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Assessment of Land Cover Change in
North Eastern Nigeria

School of Applied Science

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Abstract

Land cover change provides a means of understanding and managing the problems of degradation and shortage of land and water resources and the conflicts therewith in the north eastern Nigeria. This research assessed how tree, shrub grass, bare ground changed from 1986 to 2005 using the NigeriaSat-1 and Landsat images calibrated with field survey data. Thirteen subclasses of the land cover were spectrally analysed and classified severally, however uncertainties in the classification made the merger into four classes necessary. Changes were analysed according to persistence, swapping, loss and gain analysis, multi-year transition of each land cover in succession, location of intensive change, and regional change density. Uncertainties were analysed by confusion and transition error matrices. The overall accuracies of the classifications were between 60% and 75%, and the transition and change accuracies were between 45% and 60%. Approximately 60% of the area of study remained unchanged during the period. Of the remainder, approximately 11% of the area interchanged between shrub grass and bare ground. Shrub grass was found to be the most unstable category and the source of most misclassification. The loss of tree was general but more intensive in the Fadama making it the most vulnerable. How local people perceived land cover change was sought through group interview and the results concurred generally with the assessment of the changes. NigeriaSat-1 imagery was tested for its quality and whether the addition of the middle infrared wavebands improved the classification. NigeriaSat-1 failed to classify the 13 classes and the middle infrared did not improve the classification, thus comparable to Landsat data, although the test was done with dry season images and the result may likely be different for wet season imagery. The 8 km AHVRR-NDVI was found to be useful in assessing the timing of image acquisition, but the data could not provide sufficient spatial resolution to warrant its usage for local scale studies.

Acknowledgment

I wish to praise God for the grace to reach this point in my life and to undertake the PhD programme. I am profoundly grateful to my country Nigeria and to Petroleum Technology Development Fund who sponsored my programme and to my employer the University of Maiduguri who granted me study leave with pay. I want to thank my supervisor Tim Brewer who patiently worked with me to produce the thesis. In this wise I wish to thank all who worked with me in the process especially Drs. Sannier and Waine and Professor J. C. Taylor. I wish to thank Cranfield University for supporting me when my scholarship expired.

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Finally, I will ever be grateful for the support the family of Mr M. Bonet gave me at the crucial moment of completing this work.

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Dedication

I wish to dedication this work to my wife Jummai and my children Joshua Bishop, Sheba, Hauwa Mercy and Mary Godiya

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Notation

AHVRR	Advanced Very High Resolution Radiometer
ANNs	Artificial Neural Networks
DMC	Disaster Monitoring Constellation
DN	Digital Number
GIS	Geographic Information System
GPS	Global Positioning System
IGBP	International Geosphere-Biosphere Programme
ISODATA	Iteratative Self-Organising Data Analysis Techniques
JM	Jeffries Matsushita
Landsat ETM	Landsat Enhanced Thematic Mapper
Landsat TM	Landsat Thematic Mapper
LUCC-MA	Land Use and Cover Change, Millenium Ecosystem Assessment
MODIS	Moderate-resolution Imaging Spectroradiometer
NASRDA	National Space Research and Development Agency
NDVI	Normalised Difference Vegetation Index
NEAZDP	North Eastern Arid Zone Development Project
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Production
RGB	Red Green Blue
RMSE	Root Mean Square Error

Chapter 1 Introduction

Land cover and land use changes are important indicators of how humans interact with their environment and how they can affect it. The drive of humans to exploit the land (land use), for survival, socioeconomic or political purposes affects the physical structure and surface features of the land, that is, land cover. The continuous changes due to the nature and circumstances of human activity, for example, population increase, and the search for more productive land, keep changing the land use and hence the land cover. For example the increase in population could lead to the search for agricultural land, which could cause the conversion of forest to agricultural land, and the expansion of the urban could lead to the conversion of the agricultural land to urban. The impact of these changes can sometimes have negative impacts, for example, the degradation of land and forestry, and climate change (Lambin et al., 2006 and Moran et al., 2004).

Land cover is the attribution of the physical properties of features on the earth surface such as forest (Moran et al., 2004), while land use is the attribution or abstraction of the way land is put to use, for example, agriculture, industry. Land cover tries to answer the questions: what are the physical features on the land, how are they distributed, how do they change over time and how will they be in the future. Land use on the other hand asks the questions: how is the land used, whether the purpose changes with time and what will it be in the future. A combined land cover and land use analysis would ask questions such as how does land use affect land cover or vice versa, or how do they affect global environmental change. The measurement of land cover changes are primarily in the realm of physical science measurements (field observation or remote sensing) while land use measurements may be in addition to the land cover analysis the measurement of the use of the land, which could require social science methodology. Thus the combined land cover and land use endeavour provides a broader means of understanding the interaction of geo-biophysical, socioeconomic systems behaviours and interactions as typified by the International Geosphere Biosphere Program (IGBP) land use and land cover program (Moran et al. 2004).

The interest in measuring land cover change has as many dimensions as the various interests of researchers. However, this could be generalised into spatial or geographical, temporal or methodological dimensions as illustrated by Ramankutty et al. (2006) in Figure 1-1. Global and regional interest in land cover is mainly directed at developing a global database of remotely sensed imagery, for example, 1km AHVRR and 250m MODIS (Loveland et al., 2000, Hansen et al., 2000) which could be used for assessing changes in land cover and hence land use (Lambin et al., 2006) and carbon cycle calculation (Moran et al., 2004 and Lambin et al., 2006). The NOAA AHVRR (1km data) has become one of the most useful datasets for the measurement and monitoring of land cover properties, for example, vegetation phenology and net primary productivity (NPP) (Tucker, 1999; Olsson et. al., 2005; Anyamba and Tucker 2005; Sannier et al, 2000). At local to regional scale the endeavour of land cover work focuses on local land change using medium spatial resolutions mainly Landsat data (Roger et al., 1997; Larson, 2000; Miller et al., 1998; Lopez et al., 2006; Braimoh and Vlek, 2005). The methodological aspect of land cover analysis is currently dominated by remote sensing (Figure 1-1), and has several variations, for example, databank, classification, image interpretation and time series analysis.

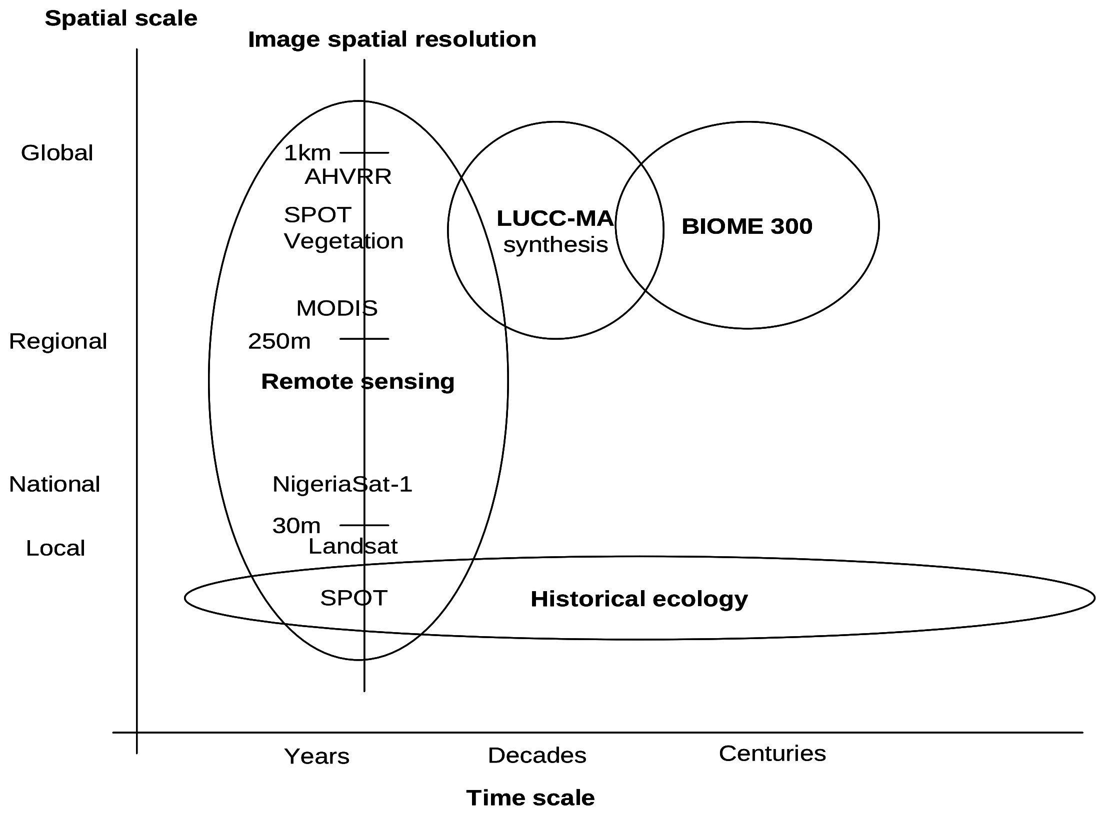


Figure 1-1: Spatial and time scale dimension of remote sensing methods, adapted from Ramankutty et al. (2006), with the addition of image spatial resolution scale. BIOME 300 and LUCC-MA are projects that investigated historical land cover changes.

Research into the application of remote sensing in land cover change analysis is either related to questions on land cover change or to the methods in remote sensing. The first asks questions that relates to the status, variability, distribution and rate of change of the land cover and its relationship to land use or natural variability. While the second asks questions related to the techniques of mapping, change detection and accuracies in the non homogeneous real world (Foody, 2002; Foody, 2006; Coppin et al., 2004; Singh, 1989).

When the application of remote sensing and land cover is directed at Nigeria, the question is also redirected to Nigeria’s needs. The focus is on what is the status and changes in land cover and their relation to land use or other factors and that of remote sensing method as it relates to the Nigerian situation.

The basic land cover need in Nigeria is the lack of a land cover database for natural resource management which could be used to mitigate local environmental problems. These problems and the need for such data are highlighted in government documents such as the vision 2010 (Shonekon, 1997). The natural resource management database that would inform professionals like regional and town planners and resource managers are not available, hence decisions are made on false assumptions (Abdalla, 1994). More than ten years after the works of Abdalla (1994) and Lawan (1996), the problem remains substantially unsolved in spite of various claims by the Nigerian government to upgrade the land use and land cover maps (Federal Republic of Nigeria, 1999); there are still complaints about the lack of such maps (Adedoyin, 2004, Mengistu and Salami 2007). Although there are maps that exist, dating back to the 1960s and 70s, the time gap makes them outdated and only useful for historical analysis. Recent land cover work such as in the Sokoto Rima Basin in 1988, Abdalla (1994), Lawan (1996), and Mengistu and Salami (2007) may also be outdated or do not cover certain parts of Nigeria. Thus the requirement to update and expand the scope of existing land cover data.

Nigeria has several environmental problems that are related to land cover change such as flood, desertification, drought, and forest degradation (Shonekon, 1997) in which the input of land cover data will provide a systematic data source to help mitigate them. Since an approach would require information and knowledge about environmental problems, this is where land cover research is important.

The north of Nigeria is one area that is known to suffer from the lack of current land cover data although it struggles from serious environment changes. This area falls within the Sahel and the Sudan savannah (Figures 1-2 and 1-3), and is affected by desertification and drought, and land use practices such as shifting cultivation and grazing that leads to soil degradation (Abdalla 1994). This is the question, which both Abdalla (1994) and Lawan (1996) attempted to answer emphasizing the applicability of remote sensing. However, the works of Abdalla (1994) and Lawan (1996) were limited to the neighbourhood of the River Komadugu in Yobe (Figure 1-2), and confined to the NEADZP (North East Area Development Zone Programme) area of Yobe state, Nigeria. Since these works were limited and not the complete representation of the state nor of the region, there is the need to study the area to the south away from the Fadama ('area susceptible to seasonal inundation', Abdalla, 1994) in order to find out whether there are land cover changes and whether the changes vary across the region.

From the perspectives of remote sensing, Abdalla (1994) and Lawan (1996) developed a land use and land cover map and tried to establish an operational procedure for using remote sensing and GIS for the area. They were able to undertake the land cover and land use classification with an overall accuracy of 65 to 70%. Abdalla (1994) further undertook a change analysis between the 1970s and 1980s. Their works tend to emphasise the classification aspect of the remote sensing. This also raises another question, since their works were more than 10 years ago and limited in their spatial scope, what change has occurred since their research with an emphasis on the dynamic aspect of land cover.

Establishing historic land cover change by remote sensing in north eastern Nigeria and indeed the whole country is challenging because there are few historic remote sensing data and where there is historical satellite data there is no corresponding ground reference data. Where the historical imagery is available, they are often separated by long time gaps (Mengistu and Salami 2007; Abdalla, 1994; Lawan, 1996). While detailed categorical analysis could be undertaken with two images at any two given times, a lot of detail could be missing in between the image acquisition times. The question could be asked as to whether the availability of NOAA-AHVRR, though of coarse spatial resolution, could be used to provide a certain insight between the higher resolution image dates. Some of the envisaged possibilities are in the mapping of local pixel anomalies within a neighbourhood (Budde et al., 2004) to detect where changes had occurred, and use of time series to detect when the changes happened and for how long (Tottrup and Rasmussen, 2004; Fuller, 1998; Jonsson and Eklundh, 2002).

The launching of the NigeriaSat-1 satellite in September 2003 marked a new phase in land cover enterprise in Nigeria, as it has contributed to the availability of data such that by early 2008 up to 82 researchers within Nigeria have benefited, many of whom would have had difficulty purchasing images from Landsat, for example (Francis, 2008). In the early stage of the NigeriaSat-1 programme, the National Space Research Development Agency (NASRDA) sponsored a project called "Validation of data from NigeriaSat-1" which was followed later by a workshop in Abuja in June 2004 on "*Satellite Remote Sensing and Geographic Information System (GIS) in Sustainable National Development*". The workshop papers showed that the data would be suitable for water resource management (Halilu, 2004), land cover and land use mapping (Omojola, 2004; Igbokwe, 2004), topographical maps and geological mapping (Ologun, 2004), and urban expansion studies (Omojola, 2004). However, none of the papers applied any rigorous test as to the quality of the image. The observations were mostly visual comparisons with Landsat imagery. Only one of the papers reported overall accuracies out of the six that reported image classifications. There is therefore a need to rigorously investigate both the applicability and quality of the NigeriaSat-1 for land cover assessment.

In summary, the need to manage land resources locally and provide input to global understanding of the environment requires accurate understanding of land cover and land use dynamics. The data required for this in Nigeria is haphazard and not currently available in many parts of the country especially the north eastern part. In the north east, the occurrence of drought and desert like condition have caused changes that need to be understood so that resources management and mitigation programmes such as tree planting, can be undertaken systematically and effectively. This research focuses on the aspect of understanding the dynamics of land cover using remote sensing methodologies. The research wishes to first answer the questions: what are the existing land covers, how are they distributed and how have they changed in the north eastern part of Nigeria from 1986 to 2005. The second question is to investigate whether there are any differences between the use of NigeriaSat-1 imagery in the classification of land cover in the north east and of using Landsat. Thirdly, how can remote sensing methods be improved for land cover classification in environments typified by north eastern Nigeria.

This study attempts to contribute to the understanding of the distribution and changes in land cover in north eastern Nigeria with the hope that it will provide a means of articulating the environmental changes occurring in the area at local scale, which could help in developing specific objectives, for example, targeted tree planting, and the evaluation of such policies. The study also tried to update and expand the earlier studies by Abdalla (1994) and Lawan (1996), by providing current land cover characteristics in an area similar to theirs in part, but much more the present study encompasses an area stretching to the southern part of the region and hence the characterisation of the land cover beyond the neighbourhood of the River Komadugu.

1.1 Aims

The aims of this research are to map current and historic land cover in north east Nigeria using remote sensing and to critically assess changes in land cover over time and thus provide data for environmental management of natural resources to aid mitigation of negative impacts of land use and climatic variability.

1.2 Objectives of the Research

The objectives of the research are to:

1. To develop a reference dataset for digital classification and accuracy assessment within the study area.
2. Produce land cover maps of 1986, 2000 and 2005 around the Potiskum area in north eastern Nigeria.
3. Analyse spatial and temporal changes in land cover during the period.
4. Analyse the accuracies of land cover classification and the accuracies of land cover transition and attempt to improve them.
5. To compare the image quality from NigeriaSat-1 and Landsat for classifying land cover in north eastern Nigeria.

1.3 Study Area

Although north eastern Nigeria was targeted for the study, the area defined politically as the north east was too large for this study. In Figure 1-2 the north east zone comprises Borno, Yobe, Gombe, Bauchi, Adamawa and Taraba states which cut across the Sahel, and Savannah regions with a combined area of about 272,395 km^2. Therefore a manageable area was chosen that fell across the Sudano-Sahelian region and Sahel (Figures 1-3 and 1-4), this being the region that experiences desert like conditions and long drought. The boundaries of vegetation or climatic zones in figures 1-2 and 1-3 are not definite since they vary with time. However, they serve to illustrate the location of the study area in accordance with the purposes of the maps. Therefore a representation of the north east that stretched across the Sahel and Sudan savannah was selected, the choice was limited to 100km by 50 km (with the geographical extent shown in Table 1-1) being an area that could be covered by a field survey team between April and June (the time the research had for fieldwork before the beginning of the rainy season). Furthermore, the area selected was restricted by the availability of NigeriaSat-1 data for the year 2005.

Table 1-1: Study area extent in projected (UTM WGS84 (32)) and geographical coordinate systems

	X(m)	Y(m)	Latitude ° ′ ″	Longitude ° ′ ″
Upper left	**671904.17**	**1329167.78**	**12 01 09N**	**10 34 45E**
Upper right	**713755.72**	**1356407.11**	**12 15 47N**	**10 57 55E**
Lower right	**768376.36**	**1272644.26**	**10 30 07N**	**11 27 37E**
Lower left	**726527.32**	**1245344.88**	**11 15 30N**	**11 04 30E**

There are two climatic seasons in the study area: the wet and the dry seasons. Generally, the wet season is between May and September. There is only one rainfall station in Potiskum that recorded a yearly average of 620 mm from June to October. There is also one at Alkali (410 mm average annual rainfall from June to October) about 80 km north of the study area and at Fika (600 mm average annual rainfall from June to October) about 20 km south of the study area (Yobe state Ministry of Agriculture, 2005).

The Potiskum area has the highest population density in Yobe state but it reduces as one moves northward or southward but certainly there are more settlements to the south of

Potiskum than in the north. This high density may have a direct impact on land use especially farming and grazing.

The study area could be divided into four physiographic areas (figure 1-4): The first is the Gamawa-Jakusko, named after the two major towns slightly north of the study area, and lies between the two tributaries of the Komudugu-Yobe river. It is made up of glysols (Sonneveld, 1997). The Fadama is the flood plain of the River Komadugu gana. The river flows from Kari from June to August and passes by the study area between October and December and then flows into Lake Chad (Goes, 2005). The Potiskum plain, made up of nutisol soils, is the land which lies between the Fadama and Gudi-Jonga hills. This area has the largest urban centre in the area. The Gudi Jonga hills in the southern part form the fourth physiographic region which is hilly and with higher vegetation density. Each of the areas in some ways represents north eastern Nigeria: the dry north closer to the Sahara, the Gudi-Jonga hills in the south represents the savannah region, while the Potiskum plain the transition zone between the Sahel and the Savannah. Although political boundaries are not significant in the physiographic context, nevertheless the boundary of the local government that lies central to the study area was included. The extent and shape of the whole study area was chosen to fit a systematic sampling procedure.

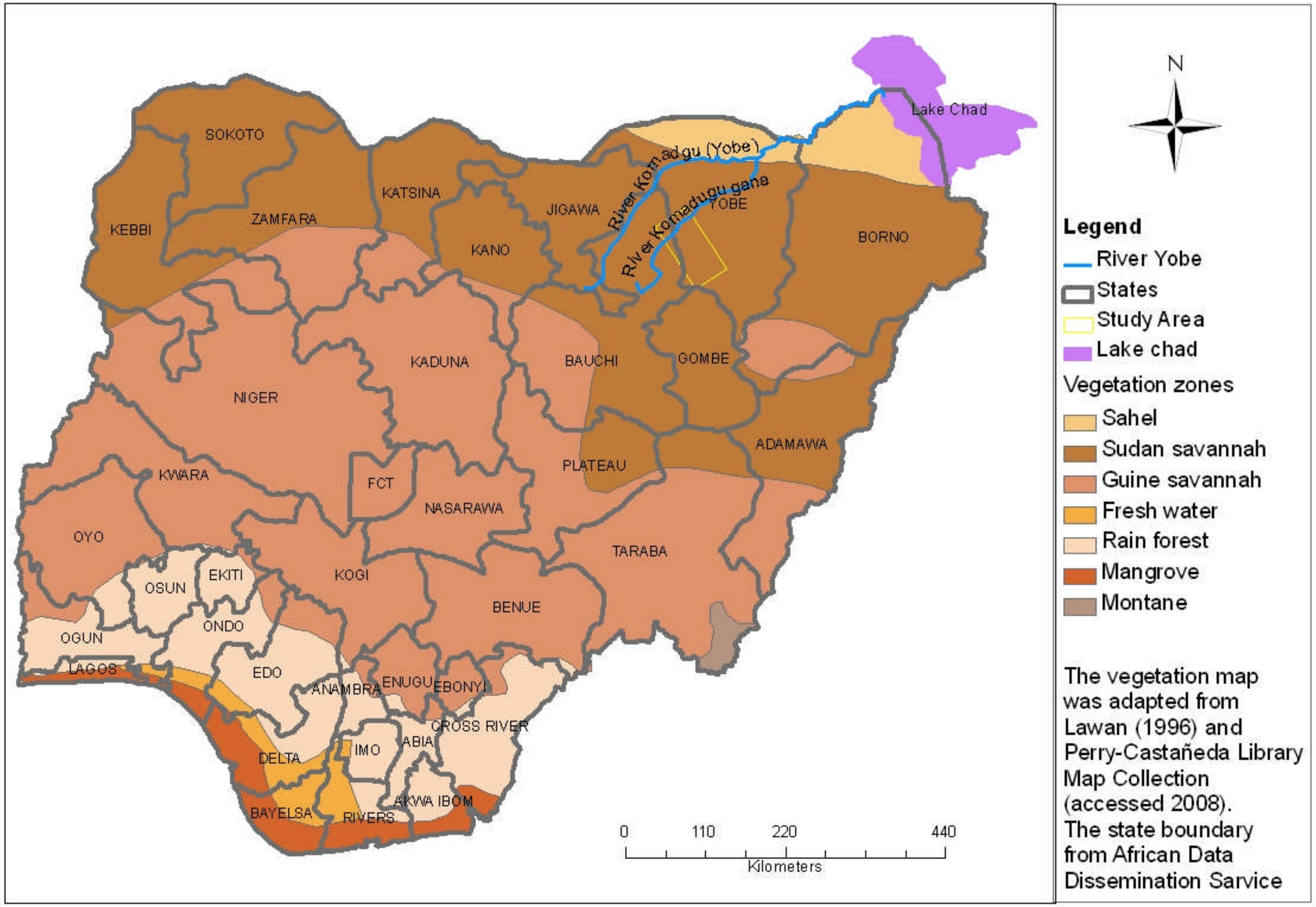


Figure 1-2: Political and vegetation map of Nigeria. The River Yobe, Lake Chad and the study area are shown.

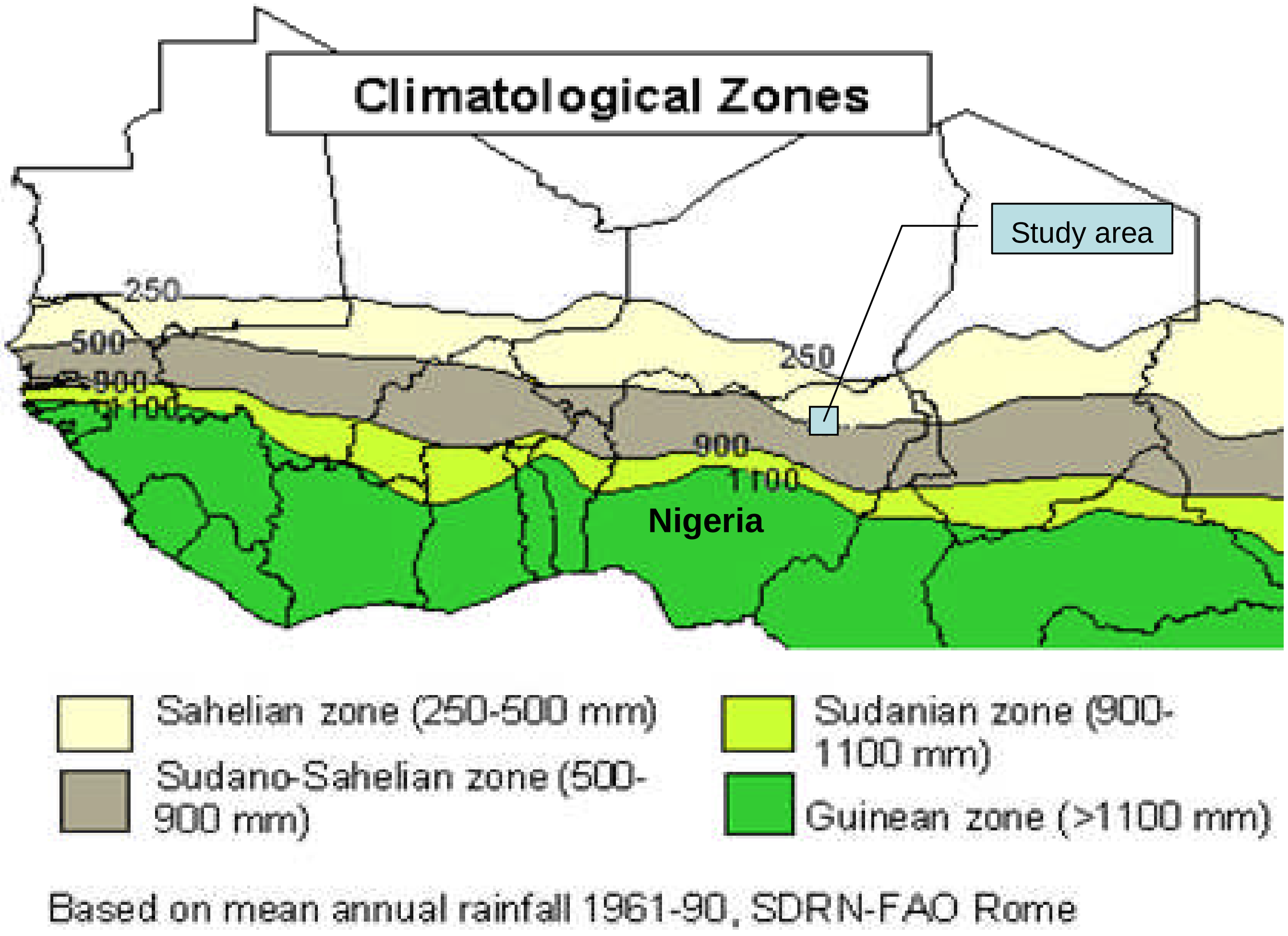


Figure 1-3: Climate zones of West Africa, (accessed from http://www.fao.org/docrep/006/J2517e/eSah-cl.gif)

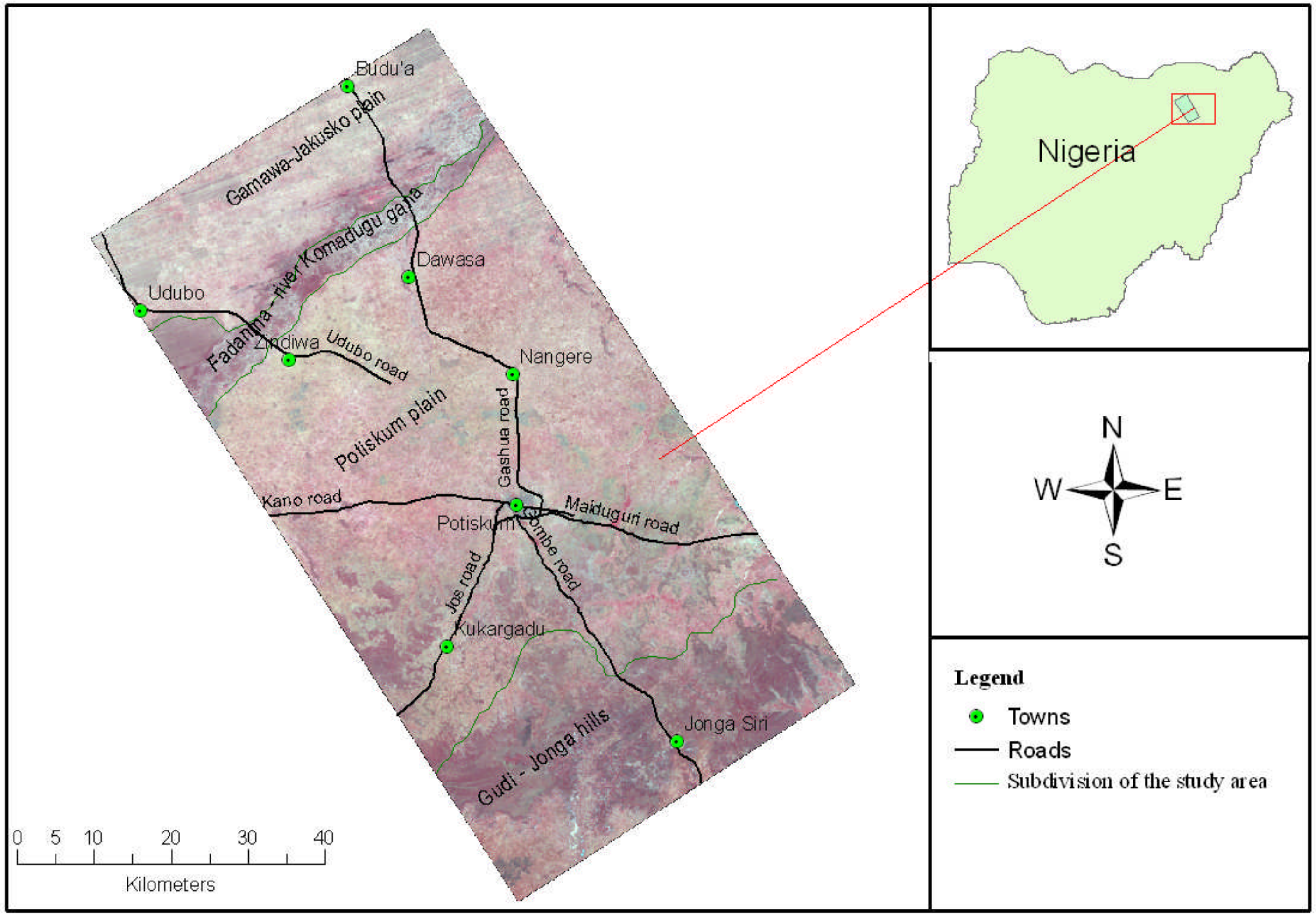


Figure 1-4: The study area divided into four physiographic regions (Gamawa-Jakusko plain, Fadama, Potiskum plain and Gudi-Jonga hills). The insert indicates the location of the study area in Nigeria.

1.4 Scope and Limitations

It is challenging to analyse land cover change in Nigeria (923,768 sq. km), or even the north east. Thus this research was limited to only a part that represents most of the land cover types that can characterize the north eastern region. The time available for the field survey conducted mainly by the researcher and one assistant within 3 months limited the spatial extent that could be studied.

The remote sensing data available only relates to the dry season and the survey was also conducted during the same season. During this period the cropland is inactive and hence much bare ground is likely to be present. Secondly the vegetation is under stress from high temperatures, and the grasses are usually dry. However this is the time when the satellite data could be acquired with the effect of cloud minimised.

1.5 Overview of the Thesis

Remote sensing creates a representation of the real world by capturing and recording its reflective properties. Its ability to detect the different reflectance of features of the real world provides the basis for its use. It is able to produce a representation of the world and that provides material for its study, since it is economically viable and in many instances the only viable way to reach certain parts of the world.

The need of this research to detect and examine changes relating to specific land cover and to have individual classifications at certain points in time before analysing the changes suggests the use of supervised classification. The following are the general steps followed in conducting a supervised classification (Richards and Jia, 1999; Lillesand and Kiefer, 2000: Schowengerdt, 2007).

a) Propose land covers of interest;

b) Select suitable image data to be used, and probably conduct feature extraction;

c) Extract training data and generate spectral signatures suitable for the classifier of interest, and evaluate the spectral signatures;

d) Conduct the classification and produce thematic maps; and

e) Evaluate the classification.

In this research the selection of land covers of interest was open to any land cover that existed in the study area and could be classified by NigeriaSat-1, Landsat ETM+ and TM, that was also comparable and compatible to an existing land cover classification system, and that would be suitable for the mitigation of environmental problems and the management of land resources in Nigeria. Thus the selection of the land covers of interest was dependent on what land covers existed in the area. Therefore one of the strategies that would meet this requirement was to draw from an existing classification scheme and then test it in the field (or aerial photo).

At this juncture the issue of sampling arises because it is not possible to cover the whole study area on the ground, and where that is possible, it counters the fundamental rationale of using a remote sensing method: that classification could be achieved with few sample data (Sannier, 2000). Thus sampling is conducted in order to train classifiers and conduct mapping accuracy analysis.

The idea of training can be conceived as follows: samples of land covers are selected and their characteristics drawn (spectral signature) of each land cover and used as input into a classifier that will transform the image into a land cover map. The development of the training material for the NigeriaSat-1 imagery is discussed in chapter 2, while the training material for Landsat ETM+ and TM are discussed in chapter 4. The classification i.e. transformation of NigeriaSat-1 is discussed in chapter 3, and the Landsat data in chapter 4.

In acquiring the training data, the data for testing the accuracy of the mapping is acquired. This is crucial in this research, because of the cost implication of acquiring the trial and testing data separately. Hence sampling was done in order to meet the requirements of the two at the same time.

Land cover changes are analysed from the three image dates available: NigeriaSat-1 for the year 2005, Landsat ETM+ for the year 2000 and Landsat TM for the year 1986. The changes were analysed according to the land cover categories and the transition amongst the classes. This is presented in chapter 5. The other purpose of these analyses is also the analysis of the NigeriaSat-1, that is, how well is it able to classify the data and how it differs from the Landsat data. This is discussed in chapter 4. The supplementary role of the NDVI time series is also discussed in chapter 5 and finally the conclusions and recommendations are presented in chapter 6.

Chapter 2 Creation of Reference Field Data for Classification Training and Accuracy Assessment

2.1 Introduction

This research comprised of the classification of NigeriaSat-1, Landsat ETM+ of 2000 and Landsat TM of 1986. It also analysed the changes between the classified images so as to produce land cover maps and a statement of change for the period of the study (Figure 2-1). The classification process was preceded by development of data that was used for training of the land cover classifier analysis from the spectral signatures of the training data.

Training the classifier required data that helped identify land cover classes of interest. Because such data did not exist and also because similar data would be required during accuracy assessment, it was considered better to produce a reference dataset from which both data could be acquired. This would avoid the cost of returning to Nigeria and conducting another field survey. Thus the focus of this chapter is the production of the reference data. It first deals with the definition of the land covers of interest, followed by the sampling procedure and the planning of the field survey, undertaking the field survey and finally the compilation of the field results.

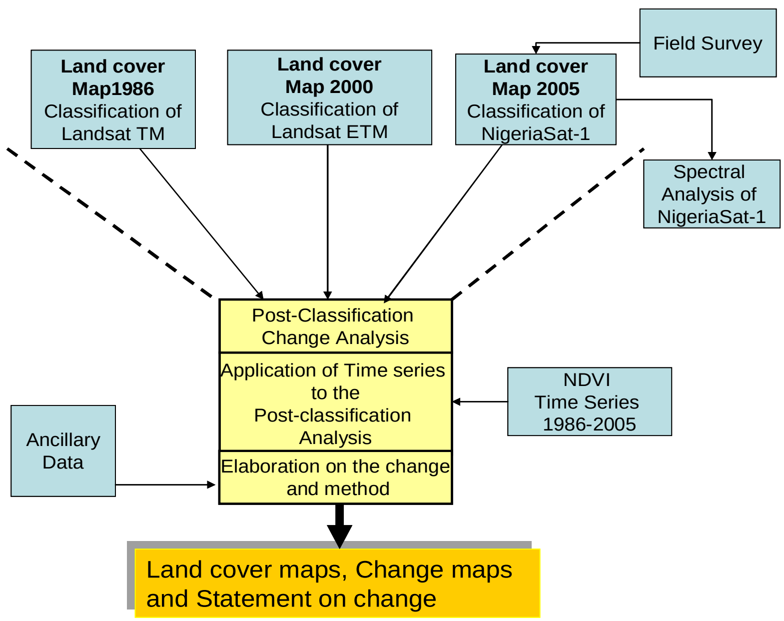


Figure 2-1: Summary of the research methodology.

2.2 The Classification Scheme for Mapping Land Cover in North Eastern Nigeria

Land cover classification is a scientific process of categorizing land related features into meaningful groups for understanding the land cover related patterns and processes, and the impacts of such processes. This implies that a definition of the grouping or in this case the land covers that do exist should be defined. It is this definition of the land covers of interest so arranged that provides what is often called a classification scheme.

The objectives of this research do not focus on specific land covers. However, it is interested in the land cover that would help in the understanding of the environmental problems and their mitigation. Because these problems are broad (for example, degradation of natural resources), and also the need of land cover information may be broad, it will be useful to produce a land cover map that will also be broadly based and can be obtained from the images available. Furthermore, some classification schemes already exist (e.g. Anderson et al., 1976, Gregorio and Jansen, 2005, Lawan 1996). It was therefore sensible in this research to produce a land cover classification that would be compatible to existing land cover data, as this makes it easier to analyse across time and space.

It is also sensible to draw from existing land cover schemes such as Abdalla (1994), Lawan (1996), and Gregorio and Jansen, (2005), as this reduces the effort that would be spent in developing a classification scheme from first principles, while drawing from existing schemes has the advantage of being consistent with other users of the system. The drawback of this approach is the possibility of misunderstanding the system, especially the definition of the land covers, which could lead to error (Comber et al., 2004; Prenzel and Treitz, 2005). It is therefore necessary to understand the key issues relating to most land cover schemes whether one can extract or modify an existing scheme or create a new scheme.

The scheme developed in this work was achieved by modifying an existing classification scheme, this was because there were similarities (research objectives, geography and image resolution) between this work and that of Lawan (1996) and Abdalla (2004). However there are variations due to the original purpose of Lawan's and Abdulla's studies and variation in the spatial extent and location of the study area. Modification became necessary because their original purpose and the scale of study did not match the need of the current project (Gregorio and Jansen, 2005; Lawan, 1996; Su, 2000). When Lawan (1996) developed a classification scheme, he reviewed earlier classifications related to his area of study and found that the classification scheme of Yangambi (1956) (in Lawan, 1996) was imprecise in class definition, the Overseas Development Agency (ODA) classification scheme was designed for land suitability, the NIRAD classification was based on eco-climatic zoning (e.g. Figure 1-2) and lacked water related land use. His approach was to draw the nomenclature from NIRAD and the others and to add water related classes from the Sokoto Rima project.

In designing or adopting a scheme some factors ought to be considered:

1) Identify whether the mapping process is based on remote sensing methods or just field survey. If it is the former, as is the case in this research, then what is the spatial resolution of the data? This is because in classifying urban for example it is not possible to analyse components of the urban class with a Landsat image of 30m spatial resolution. The matching of image resolution and the level of classification (e.g. Figure 2-2) are discussed in Jensen, (2000) and Schowengerdt (2007).

2) Identify whether the mapping will use a hierarchical or a non-hierarchical scheme. A hierarchical scheme organises land cover in order of hierarchy, thus a higher level class is made up of several subclasses, for example Figure 2-2. A hierarchical scheme permits multi-scale usage, for example, usage at one level only or all the levels (Gregorio and Jansen, 2005)

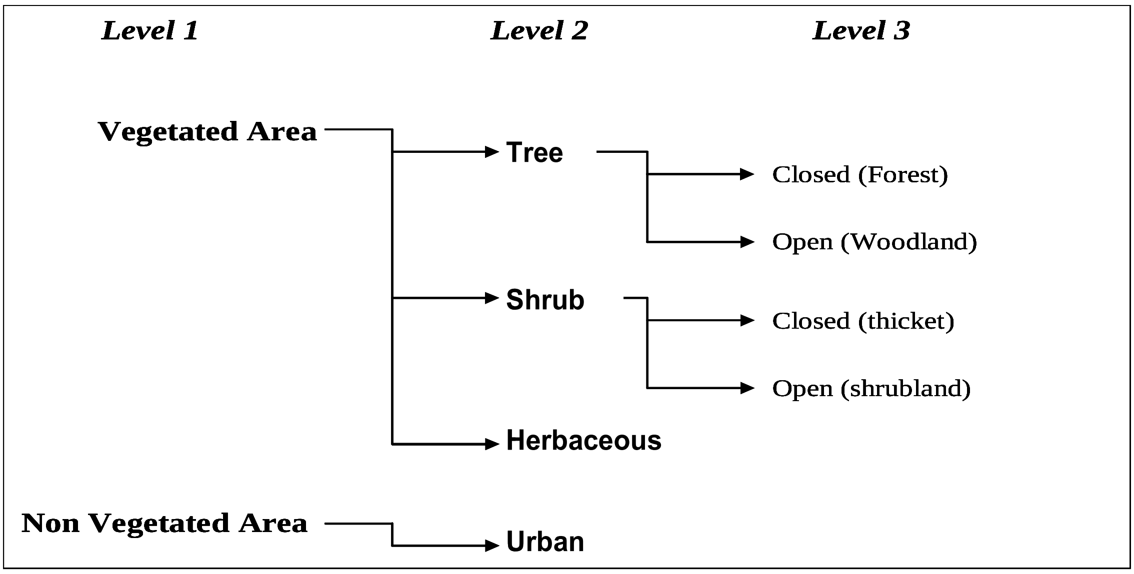


Figure 2-2: Example of part of a hierarchical classification scheme.

3) Identify whether it should be an *a priori* or *a posterior* classification scheme. This is a choice between designing and adopting a scheme prior to or after the field survey. The former has the advantage of having a standard scheme irrespective of location but the disadvantage of being rigid. However the latter has the advantage of flexibly defining classes during survey but may fit to a standard classification scheme (Gregorio and Jansen, 2005).

4) That the criteria should unambiguously define each class (Gregorio and Jansen, 2005).

This research modifies the schemes adopted by Lawan (1996) and Abdalla (1994) (the classifications are almost the same except for differences in some of the nomenclature) because: (1) the purpose in this research and theirs is similar, that is, the mapping of land cover and (2) both are in the same region and share part of the same catchment of the River Yobe although their area is about 50 km north. Thus most of the land covers are expected to be similar. However, it was necessary to modify the classification because: (1) their schemes incorporate both land use and land cover while the emphasis in this research is on land cover; and (2) their study areas were limited to the neighbourhood of the River Yobe, while this study stretches southward further away from the river's neighbourhood.

The modification was done by reviewing the structure, definition and the guidelines on classification development in Gregorio and Jansen (2005). The modification affected mainly the classes associated with cultivation (Table 2-1). The area used for cultivation of crops was modified to crop land, and the bare uncultivated land was simply changed to bare ground. Thus crop land means land with crops and not the land used for cropping. A particular change was made to the tree and shrub land covers by introducing the term high tree (mixed) and short tree (Taylor et al., 1996), as well as high and short shrub. This was in anticipation of variation of plant structure between the north and the south of the study area.

The modified classification scheme is presented in Table 2-2 with the following clarifications:

1. That the term tree refers to 'woody perennial plants with a single, well-defined stem carrying a more-or-less-defined crown' (Ford-Robertson, 1971

in FOA-Africover, 2007). The lower limit of tree height should be on average 3m (similar to FOA-Africover, 2007) and a 40% cover of the area (FOA-Africover, 2007), a situation where from a distance the tree would be looked upon as an entity, it overrides whatever percentage of shrub.

a. The riparian tree, trees along water bodies, share the general characteristics of the tree class except that they are associated with water bodies and not inundated in water. The definition of riparian was limited to perceived association, this was because the class was among the least encountered in the field survey by Lawan (1996), and the emphasis of this work is not the types of the riparian vegetation. It was assumed that if the class existed, it would be spectrally different from the other trees because of the closeness to water.

b. Marshy woodland is where the trees are inundated by water.

c. Orchards are distinguished (distinguishable in Warner and Steimaus, 2005) from the tree class by it being planted. This study assumed that because the trees used in orchards within the study area were limited to a few types, for example, mango and guava with high densities, that these characteristics would distinguish orchards from the other trees, although orchard is a type of land use.

d. High tree savannah (mixed), a name adopted from Taylor et al. (1996), refers to high trees that are above 5m on average and contain a variety of species.

e. Short tree savannah (Taylor et al., 1996) is a class of trees that are on average above 3m but less than 5m.

2. The shrub class is distinguished from the tree class in terms of having several stems and generally being shorter than trees. Shrub is grouped together with grass simply because they differ from tree and often coexist. They are distinguished by their coverage, as with the tree class, to at least 40% coverage (FOA-Africover, 2007). The exception being when there is

more than 40% tree, then tree takes pre-eminence whatever the proportion of the grass or the shrub. Four types of shrub were distinguished: high shrub mixed, where the shrub dominating the landscape was more than 2m high on average; short when the shrub was less than 2m high; marsh bush when it was inundated with water and a dumb palm dominated shrub. If however there seemed to be an equal covering of shrub and grass it was considered as shrub grass, else grass when grass dominated the landscape.

3. Although both the field survey and the image were taken during the dry season, no crop was expected, but because of the dry farming activities in the Fadama area provision was made for the two main crops being farmed, that is, rice and wheat (Lawan, 1996).

4. Dry bare surfaces were classified simply as their appearance into bare ground, bare ground clay, bare ground gravel and bare rock.

5. Developed areas were categorised into three classes: towns and village, isolated settlements and roads.

Table 2-1: Modification to level 1 of Abdalla (1994) and Lawan (1996) classification schemes

Abdalla (1994) Classification	Lawan (1996) Classification	Modified to
Water Bodies	Water	Water bodies
Wood and Forest Land	Woodland	Tree land
Shrub and Grass Land	Shrub and Scrub Bushes	Shrub and grass
Cultivated	Floodplain Irrigation	Crop land
	Non-Floodplain Irrigation	
Bare Uncultivated Land	Bare Land	Bare land
Developed Land	Developed Land	Developed land

Table 2-2: Classification scheme developed for land cover mapping in north eastern Nigeria

Categories	Subcategory	Description
A. Water Bodies	**River, lakes, ponds**	**A stream or standing body of water**
B. Tree land	**Riparian tree**	**Trees along water channels**
	Marsh woodland	**Trees inundated by water**
	Orchard	**Collection of planted trees**
	High tree Savannah (mixed)	**Collection of trees, taller than 5m**
	Short tree Savannah (mixed)	**Collection of trees more than 70% mixed species , 3m – 5m tall**
C. Shrub and grass	**High Shrub (Mixed)**	**Shrub more than 2m tall, mixed species**
	Short Shrub (Mixed)	**Shrub less than 2m tall, mixed species**
	Dumb Palm Bush	**Shrub like bush mainly dumb Palm**
	Marsh Bush	**Inundated shrub in water**
	Grass shrub	**Mixture of shrub and grass, more than 30% of each**
	Grass	**Grass, more than 70%**
D. Crop land	**Wheat crop**	**Land with wheat crop**
	Rice crop	**Land with rice crop**
E. Bare land	**Bare ground**	**Bare ground, no gravel, not clay**
	Dry mud surface	**Bare ground, dry clay**
	Gravel	**Bare ground, gravel**
	Bare rock	**Bare ground, rock**
F. Developed land	**Towns/villages**	**Major settlement**
	Isolated settlements	**Small temporary settlement not less than a hectare**
	Roads	**Tarred Roads**

The scheme above (Table 2-2) fulfils the needs discussed in the introduction in chapter one at two levels according to the two levels of the classification scheme, that is, the category and sub category level. The category level provides broad baseline data which are for example equivalent to the broad habitat classification that was used to provide the census of countryside habitats in the UK (Fuller et. al., 2000). Thus the category level provides government at local, state or federal levels with data on areas of tree (or woodland or forestry), shrub grass, bare ground and urban. The monitoring of the land covers further provides data on their changing conditions and implication for food production for example (e.g. Lambin et al., 2006). This therefore can help all levels of government to understand where for example degradation is occurring, by what quantity and at what location and hence plan its mitigation appropriately. It will also help to monitor the effect of government programmes such as tree planting on whether it is succeeding or not and could provide the basis for studying the impact of land use.

The subcategory provides data on the specific types of land cover available in the study area answering the question of what land cover exists (Taylor et al., 1997; Taylor 1976) and what detail of land cover can the NigeriaSat-1 classify. The subcategories of the tree class were used to identify whether the tree structure in terms of height could be distinguished, and whether particular types of tree could be distinguished. The success in classifying the subcategory would provide a basis for monitoring a particular tree of interest. Similarly the success in classify the subcategory of the shrub grass will help in monitoring shrub types that are associated with desert encroachment (Waser et al., 2008).

2.3 Sampling Scheme

Sampling was necessary because practically it was difficult to cover the study area by field survey and because this research planned to use a remote sensing method for land cover classification. It was not necessary to cover the whole area by field survey. With a field survey of 1% sample size, remote sensing imagery can be classified and its accuracy tested (Sannier, 2000). A sample approach was therefore needed that would distribute the samples over the study area and capture the land cover proportionately and also provide for unbiased testing of mapping accuracy.

Some the standard sampling methods (Taylor et al., 1997; Gallego, 1995) used for this kind of survey are:

(1) Simple random which selects a sample completely by random (Figure 2-3 (1)).

(2) Simple random sampling with distance threshold, which although a simple random method, it prevents sampling within a certain distance (Figure 2-3 (2)).

(3) Systematic aligned random sampling divides the area to be sampled into segments or blocks, within a reference block a sample is randomly selected and then samples are selected in the other blocks systematically in alignment with the reference sample (Figure 2-3 (3)).

(4) Systematic unaligned random sampling, selects a sample randomly within the blocks (Figure 2-3 (4)).

(5) Systematic unaligned random sampling with replicates (Figure 2-3 (5)).

(6) Stratified random sampling selects sampling separately within known segments of the study area (Figure 2-3 (6)).

In both (3) and (4) sampling can be replicated with subdivisions (blocks) of the study area.

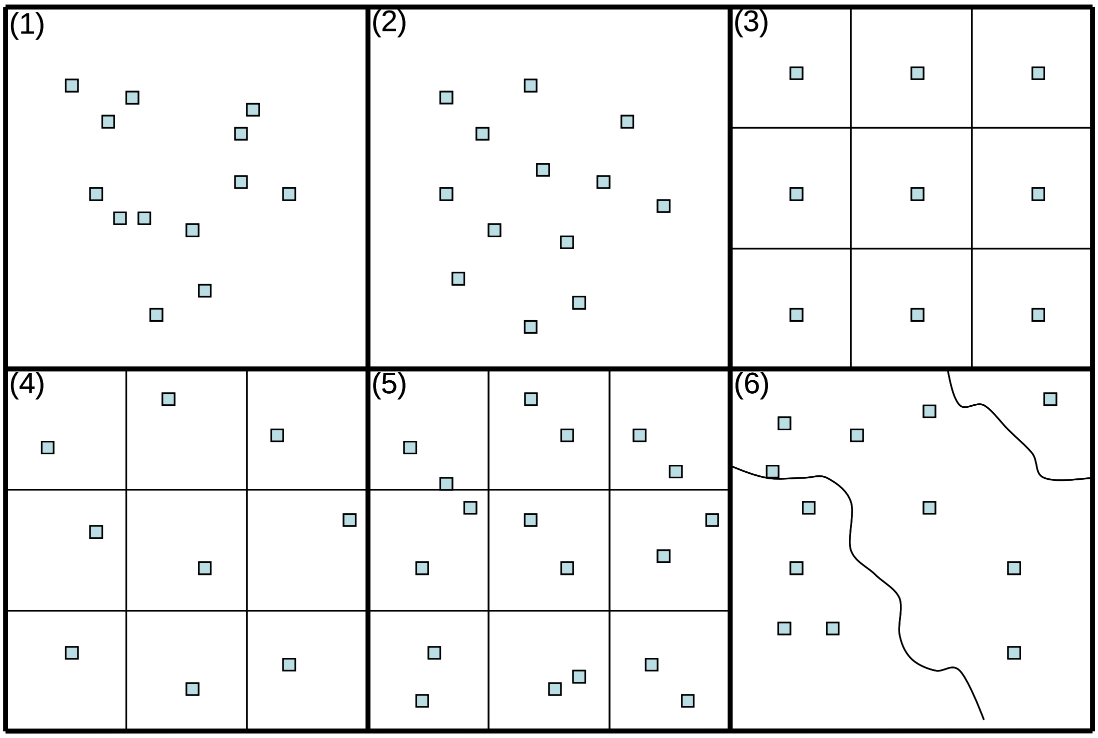


Figure 2-3: Types of sampling used for field survey for remote sensing classification, (1) random sampling, (2) random sampling with distance threshold, (3) systematic aligned random sampling, (4) systematic unaligned random sampling, (5) systematic unaligned random sampling with replicate and (6) stratified sampling (Taylor et al., 1997; Gallego, 1995).

The systematic unaligned random sampling method was preferred because it incorporated a random distribution of samples and it uniformly distributed the sample squares across the study area. It was preferred over a simple random sample because the latter could potentially skew the sample to one section of the study area and thus reduce the chance of capturing all land covers proportionately. Although the skewing problem could be solved by increasing the size of the random sample, this would counter the objective of minimising cost. The unaligned sampling method was also preferred to the stratified sampling method because the latter requires a priori knowledge of the strata in the area of study. Since this knowledge was not adequately known, the former method was selected. And finally, the unaligned was preferred to the systematic aligned methods by the repeated random sampling within each block (Cochrane, 1977; Taylor et al., 1997).

Determining the sample size and the dimension of a sampling unit was preceded by obtaining an understanding of the number of pixels required for training and testing the accuracy of the mapping (since a pixel based classification was used). Richards and Jia (1999) give the minimum number of pixels required for a maximum likelihood classifier as N+1, where N is the number of bands (dimensions) of the multispectral image. The reason for the number N was based on the need for the covariance matrix not to be singular and thus hinder the determination of the inverse of the matrix. The minimum number was raised to 10 N for practical purposes (Richard and Jia, 1999). The other consideration was the number of pixels needed for accuracy assessment. There are equations to determine the required number of pixels needed for training a classifier (van Genderen and Lock, 1977; Congalton, 1991) but this equation may produce conflicting results as noted by Richards and Jia (1999). Congalton (1991) also observed that some of the numbers from the equations are not fit for use in the error matrix, and suggested a minimum of 50 per class and between 75 and 100 when the number of classes exceeds 12.

From the practical suggestion the minimum number of pixels required for training a classifier of a NigeriaSat-1 image (with 3 wavebands) would be about 105 pixels per class, and if 10 classes were anticipated then that would equate to 1,050 pixels. Instead of aiming at the minimum number required, the sampling was approached differently following the example of Taylor et al (1997) and Lawan (1996), which provided more than the minimum number required. In this approach, a sampling unit was a square that supplied the need for training pixels and accuracy assessment with a pixel number beyond the requirement. Taylor et al (1997) used a 700m by 700m and 1km square sample dimension. This research chose the 1 km square so that it would fit with the systematic unaligned procedure selected

Further to the selection of dimensions of the sample the number of sample squares that would be adequate to ensure representation of all classes needed to be determined. Thus following the example of Sannier (2000), 1% of the study area was targeted. This was much appreciated when the number of pixels within the study area was considered (Congalton, 1991), that is, over 5 million pixels, and therefore 1% was over 50,000 pixels.

To achieve the systematic unaligned sampling, the study area was first divided into a 10 km square grid forming blocks. Each block was then subdivided into a 1 km grid, and then one square randomly selected within each block. Thus a total of 50 sample squares were selected and distributed as shown in Figure 2-4.

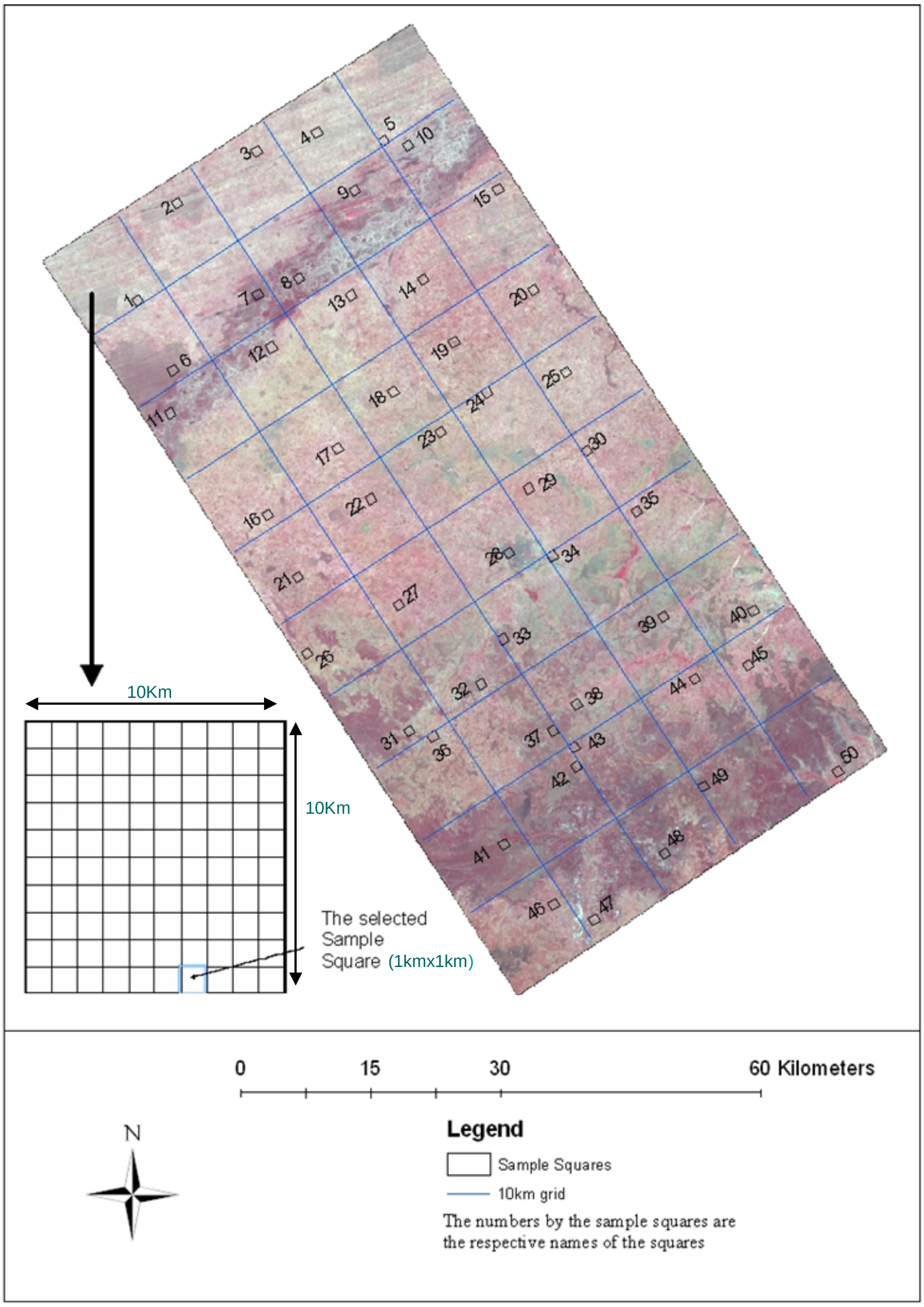


Figure 2-4: Sample squares selected by the systematic unaligned random sampling method. Each sample square was selected within a 10km block (see inset).

2.4 Field Survey

The field survey was undertaken in Nigeria between April and June 2006. This section discusses the preparation that took place, the material used during the field survey, the execution of the survey and the compilation of the field result. The preparation includes the preparation of the images, the sampling design and the daily plans.

2.4.1 The preparation of the imagery

Three images were used in the classifications in this research (further detailed in Chapters 3 and 4): the NigeriaSat-1 image and the two orthorectified Landsat ETM+ and TM images from the years 2000 and 1986, respectively, with an absolute positional accuracy of 50m (Landsat.org, accessed 2008; Tucker, 2004; Koeln et al., 1999). There was no other available map that would provide better accuracy. The Landsat ETM+ was used as the reference image. Image registration of the Landsat ETM+ image was necessary so that the coordinates of the image matched the coordinates used by the GPS to locate the position of the sample square on the ground. It was also necessary to match the image and the resulting classification to the other classifications derived from the other images so that the resulting land cover changes were not due to image misregistration.

Lawan (1996) found the manual registration of images very difficult. This was also evident in this research, by visual inspection of the images. The lack of clearly defined features could lead to poor manual location of tie points during the image registration process and thus the manual procedure would produce fewer tie points with potentially a poor distribution and low precision. Thus an alternative method was used that automatically searched for features in both the reference image and the image to be corrected (NigeriaSat-1 image), and used the features that matched as tie points (Pan et al., 2008; Chen et al., 2007; Stow et al., 2003). This process was implemented in the Erdas Imagine software using the Imagine Autosync algorithm (Leica Geosystems Geospatial Imaging LLC, 2006). The software generated 101 tie points with an overall root mean square error (RMSE) of 1.54 pixels, about 50 m .

Fifty subsets of the corrected NigeriaSat-1 image (the imagettes) corresponding to the sample square locations were printed at 1:10,000scale. On each image the boundary of the sample square was superimposed.

2.4.2 Material for field survey

The materials that were needed for the field survey are listed below:

1. An acetate overlay for the imagette on which parcels identified in the field were mapped.

2. A list of coordinates for the four corners of each sample square and twenty one other points that divided the square into 250 m by 250 m blocks (see next section).
3. A Field Note form (Figure 2-5) for recording observations.
4. A Global Positioning System (Garmin GPS 76) was used to locate points in the field.
5. A 1:50,000 guide map was developed from the Landsat ETM+ panchromatic image (2000) with towns and villages superimposed, to use as a navigation map.
6. The classification scheme as developed above.
7. A survey assistant.
8. A local guide: a person living close to sample squares.

Land Use and Land Cover Survey (Nigeria)
Field Notes:
Square ID……………………………………………..…
Location.…………………………………………..
Date…………………………………………………
Surveyors ……………………………………..……..

Parcel Code	Land cover/use	Remark

Figure 2-5: Sample of the Field Note proforma

2.4.3 Preparation for the survey

Three sample squares were generally targeted for survey each day; this number varied depending on accessibility of the squares and their distances from Potiskum (the survey base for the field work). The preparation for the field survey of a square involved the following:

1. Planning the route that would be taken to get to a sample square. This became necessary because many locations that were off the major roads were very difficult to determine how to get there because of the limitation of the existing map and the indication of several routes. Thus the plan involved inquiring how to get to a major town or village close to a square. Planning to get to the square involved asking for villages and roads that might lead to the square using the few villages evident on the guide map. This was difficult given that the people being asked may have little concept of distance and direction in the geographic coordinate sense.

2. The acetate was placed on top of the image and on it the following were marked: boundary of the square, boundaries of parcels were mapped in accordance with the shapes and patterns evident on the image, sixteen points were marked that divided the sample square into blocks of approximately 250 m by 250 m and their coordinates extracted (Figure 2-6). These points were used to provide guides and orientation for aligning the image to the field, especially where the features were not very distinct.

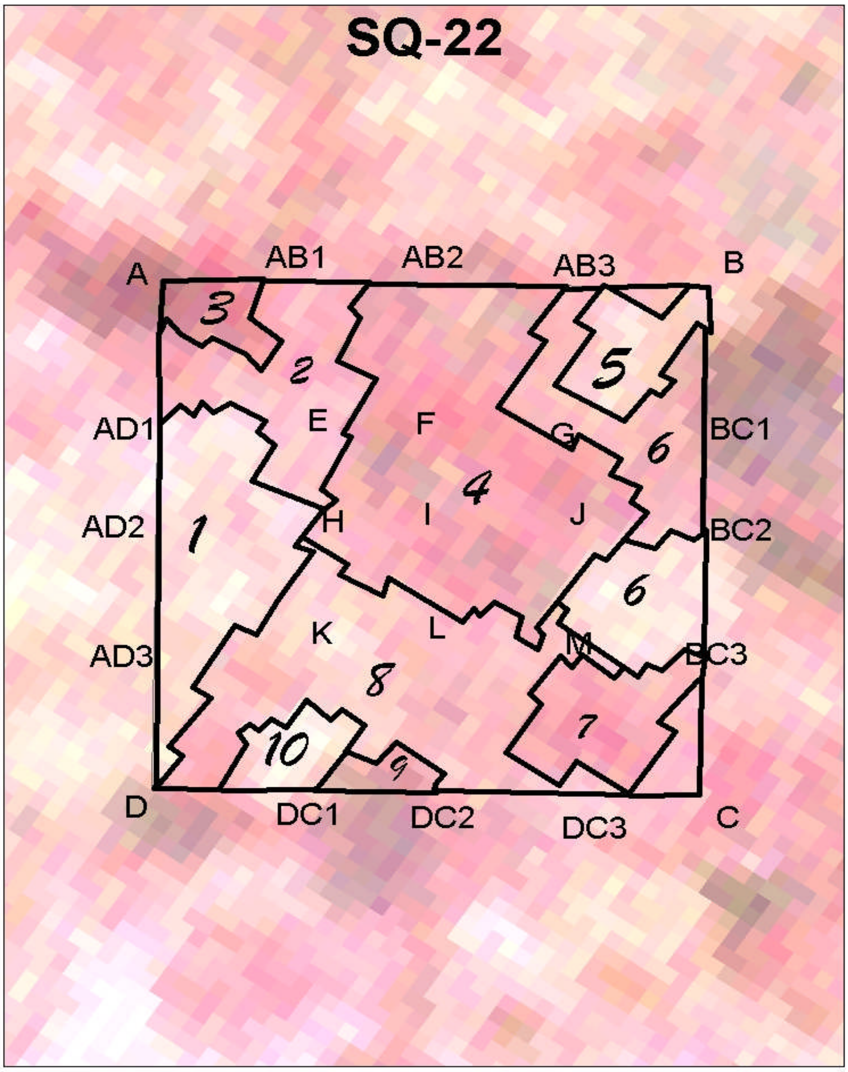


Figure 2-6: Example of a sample square image for sample square SQ-22. A, B, C and D are the edges of the square. E, F…M and AB1…DC3 are points that divide the square into approximately 250m by 250m sub squares. The numbers 1,2,..10 are parcels whose land covers are to be identified within the square.

2.4.4 The execution of the field survey

The guide map was used to direct the vehicle as close to the square planned to be surveyed as possible. The remainder of the distance was covered on foot using the GPS that was WAAS (Wide Area Augmentation System) enabled. In many instances getting closer to the square required the use of a local guide. For example, the distance between a road visible on the guide map and a square could be about 10 kilometres apart; this required a local guide to identify the route that would allow the square to be accessed.

On getting to the square, a sub-square consisting of four points (e.g. A, AB1, E, and AD1) was established using the GPS. The land cover pattern marked earlier on the image corresponding to the shape and pattern on ground; (see Figures 2-6 and 2-7a) was identified and recorded on a Field Note Form (Figure 2-7b). Each area was given a number and recorded in the parcel column, and the class of land cover was recorded in the land cover/use column and any other interesting feature regarding the parcel was recorded in the same row as the parcel. This was repeated for other parts of the square. All the 50 sample squares earmarked were surveyed in 21 working days. The difficulties experienced and other issues associated with the classification classes and the survey are outlined below:

1. The survey began with sample square number 34 which was close to Potiskum and had other features to identify in addition to the sample square as a test of the procedure. The initial plan was to set out the 1km by 1 km sample square using the GPS, in order to correctly orient the imagette and with the field information but the whole square was not visible at one time. Although this was not a problem for this particular square, it became necessary to subdivide the square into 250 m by 250 m segments for other squares to aid location and recognition of features on the ground.

2. Interpreting the high tree in the field was sometimes difficult because of openings in the canopy which were filled by low tree, grass and shrub (Figure 2-8a). The image interpretation element of a parcel in a square would show a unique characteristic indicating a particular land cover. In the field it may be a mixture although there may be a dominant class.

3. At the end of the survey the land cover encountered are listed in Table 2-3. There were new classes of land cover encountered in the field which were not in the initial classification: the short tree, kwargo, *Bauhinia rusfenscene* and shrub, sabara, *Guiera senegalense*. Thus essentially there were no changes in the earlier definition of the land cover classes (Table 2-2).

Table 2-3: Land cover classes encountered during the field survey

Categories	Class
A. Trees	**Riparian tree** **High tree (mixed) (e.g. Figure 2-8a)** **Orchard** **Short tree (mixed) (e.g. Figure 2-8b)** **Short tree (kwargo, *Bauhinia rusfenscene*).**
C. Shrub Grass	**High Shrub Mixed** **Shrub (mixed) (e.g. Figure 2-8c)** **Shrub (Sabara, *Guiera senegalense*)** **Grass shrub** **Grass (e.g. Figure 2-8d)**
E. Dry Surface	**Bare ground (e.g. Figure 2-9a)** **Bare ground clay (e.g. Figure 2-9b)** **Bare ground gravel (e.g. Figure 2-9c)** **Bare rock (e.g. Figure 2-9d)**
F. Developed Land	**Towns/villages** **Isolated Settlement**

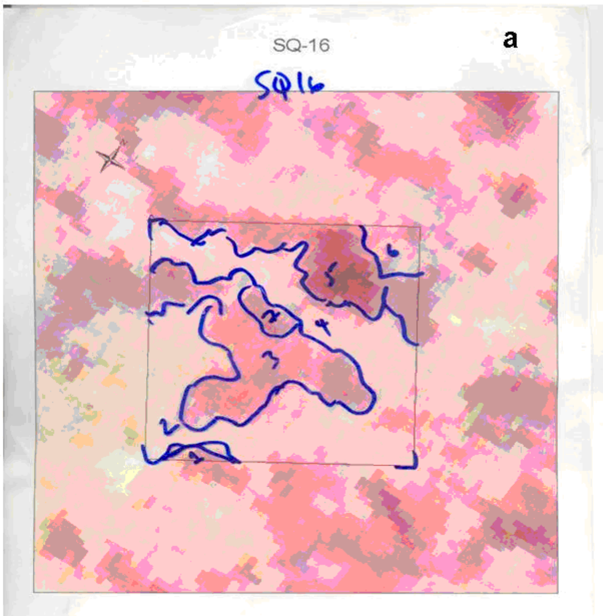
4. The efforts to get to the sample square played a very important part in the field survey although it is not evident in the final classification outputs. It will however count as part of the cost of field survey.

5. The occurrence of heterogeneous land cover undermined the principle of exclusiveness in the definition of land cover. In the field there very few instances of pure land covers: by pure it is meant that very few areas were only tree or shrub or bare land. In such instances one would often resort to the aspect of proportion in the class definition (Table 2-2). The heterogeneous class situations may have importance in depicting land covers in transition, for example, a high tree in the process of conversion to shrub grass due to tree felling or shrub land turned into bare land for farming, if that was the natural characteristic of some land covers.

6. Locating squares was one of the field survey difficulties. Sample square numbers 6, 7, 8, and 11 that lay within the Fadama, and squares 37, 38, 42, 43, 49 and 50 in the south of the study area were difficult to locate because of the

thick and bushy vegetation that would have to be traversed before getting to the square, and also because there were few settlements close to the squares and thus no access roads. In order to get to a square the vehicle would often be left some 1 to 5 kilometres from the square, the remainder of the distance was covered on foot using the GPS and the guide. A description of the direction and distance of the square was given to the guide, who suggested a village close to the squares' location from where a footpath could be taken that may lead towards the square. A similar situation also applied to all sample squares that were off the major roads. Because of the lack of current maps, it was difficult determining how to get to the squares. Even with the route plan there was still difficulty differentiating the roads. In many places the roads that end in a farm and those that went to another village or a different village than the one intended were hard to differentiate and hence one would get lost and waste time.

7. The results of the field survey were documents that included the acetate overlay with land cover parcel and number marked, and the completed field note forms (Figure 2-7) for all the 50 sample squares.



Land Use and Land Cover Mapping in Nangere (Nigeria)

Country: Nigeria

b

Field Notes:

Square ID……SQ16……………………………..….

Location……Rimi……………………………….

Date…………18th may…………………..………

Surveyors ……S. S. Clarke………………..……..

Parcel Code	Land cover/use	Remark
1	grass-shrub	
2	bare ground	Farm land
3.	grass-shrub	
4	bare ground	Farmland
5	grass-shrub	
6	bareground	
7	shrub	

Figure 2-7: Example of the completed field documents after the survey, the 'a' above is of the acetate overlaid on the imagette and the 'b' is the filled form.

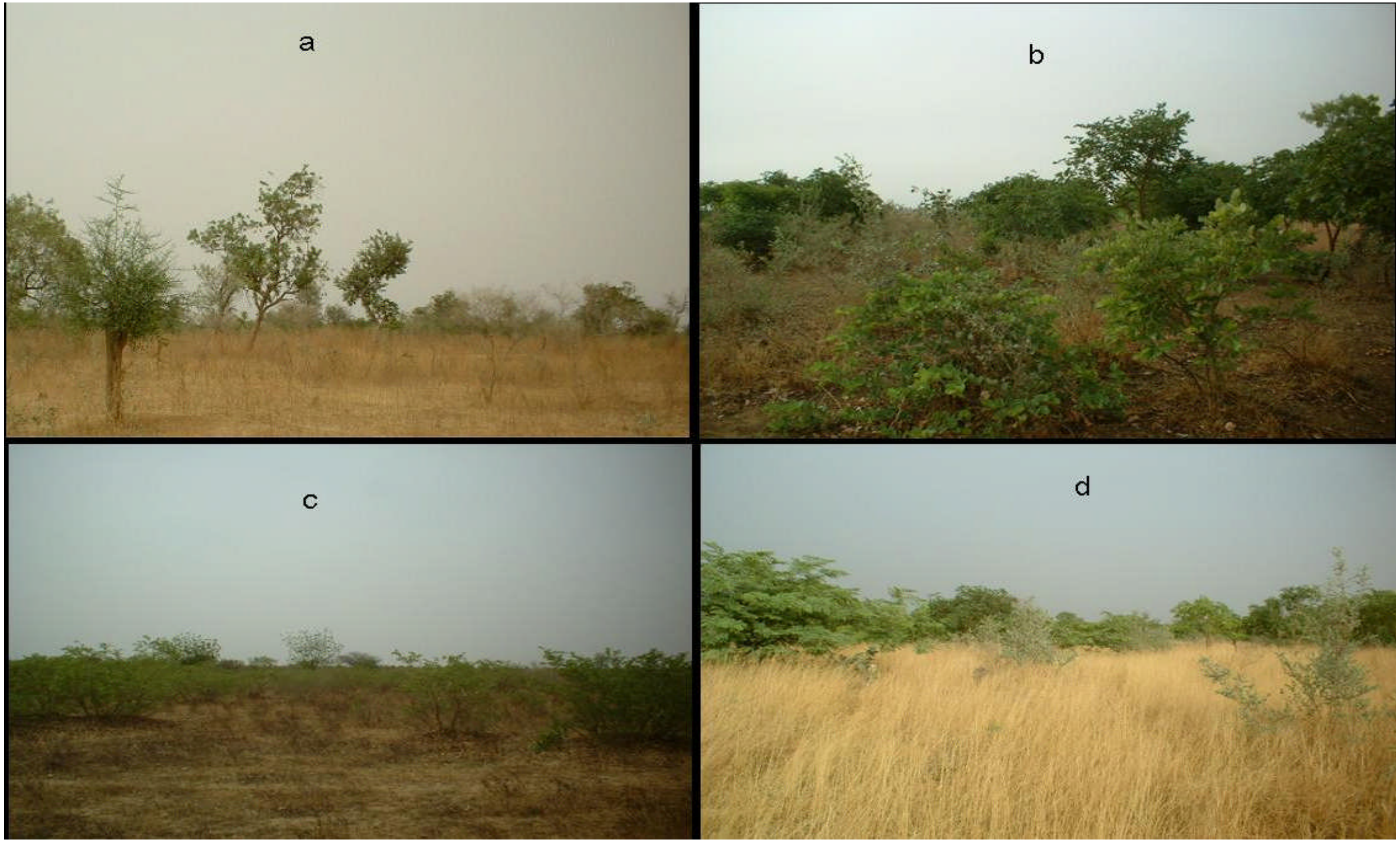


Figure 2-8: Examples of land cover types – a: High tree mixed; b: Short tree mixed; c: Shrub and d: Grass land.

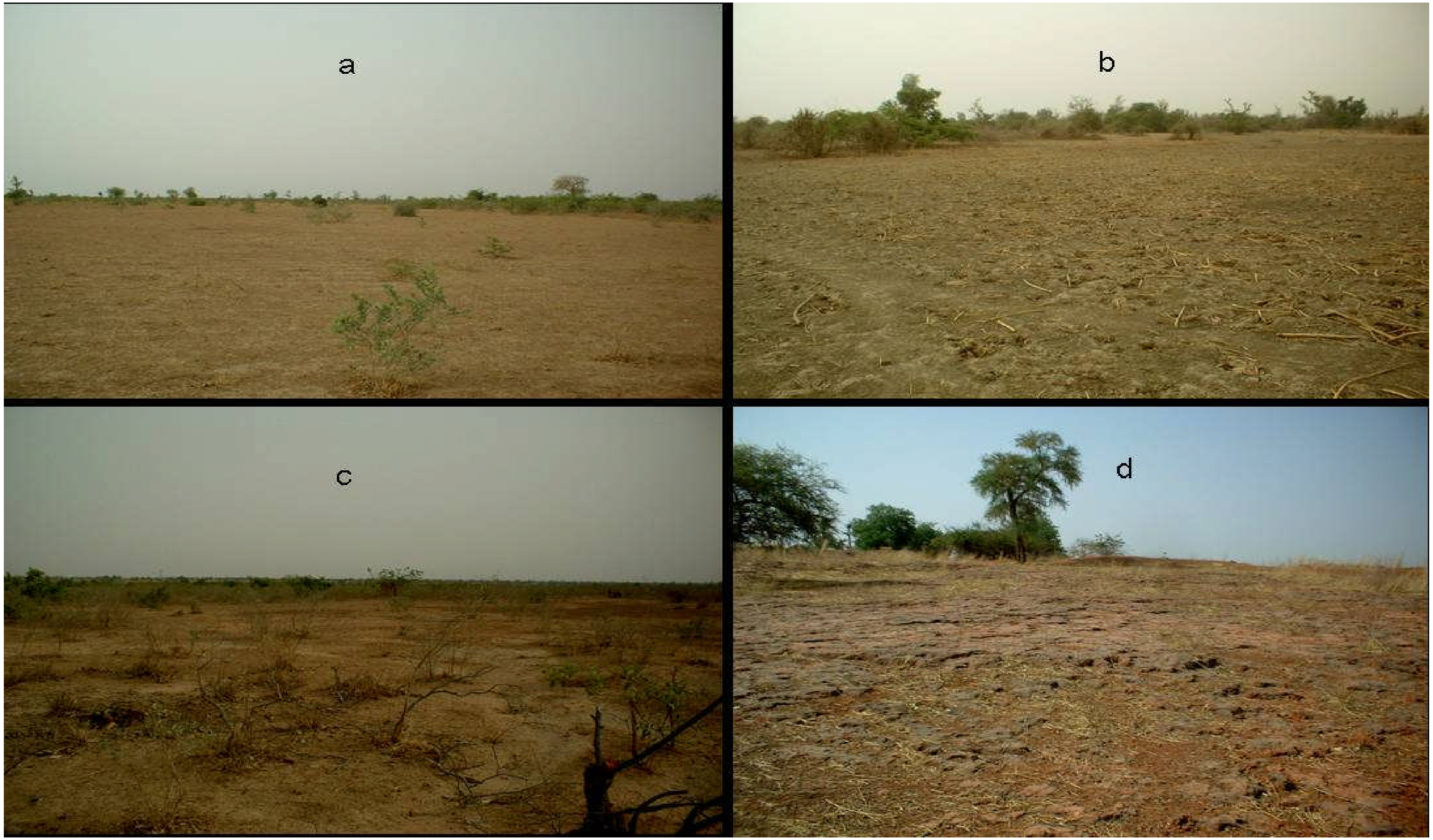


Figure 2-9: Examples of bare land cover types – a: Bare ground mostly sandy; b: Bare ground clay; c: Bare ground gravel and d: Bare rock.

2.4.5 Digitisation of the Field Survey Data

The data documented during the field survey as discussed in the previous section were digitised. Each sample square was digitised on screen and each parcel respectively attributed as in the field note. After the digitisation, the total area of each land cover was computed. The area covered by riparian tree, isolated settlement and roads was smaller than 0.5% of the overall area and less than 20 hectares scattered across the study area. It was decided that these categories were too small to provide pixels that could be used to generate spectral signatures and accuracy assessments and therefore they were merged into other classes. Table 2-3 provides the sum of each land cover mapped in the field and their percentages.

Table 2-3 Land cover areas and percentage of the total of each class from the field survey

Class Name	Area (hectares)	Area (%)
High Tree (Mixed)	**139.21**	**2.8**
Orchard	**66.81**	**1.3**
Short Tree (Mixed)	**630.99**	**12.6**
Short Tree (kwargo, *Bauhinia rusfenscene*)	**58.72**	**1.2**
Shrub (mixed)	**948.10**	**19.0**
Shrub (Sabara, *Guiera senegalense*)	**78.24**	**1.6**
Grass-Shrub	**720.70**	**14.4**
Grass	**101.72**	**2.0**
Bare ground	**1993.21**	**39.9**
Bare ground Clay	**58.08**	**1.2**
Bare ground Gravel	**53.44**	**1.1**
Bare Rock	**34.16**	**0.7**
Urban	**114.10**	**2.3**
Total	***4997.51**	**100.0**

***The 4997 hectares was short of the 5000 hectares due to the digitisation process, but that was inconsequential in the image analysis in chapter 3.**

2.5 Summary of the Chapter

A classification scheme was developed to define land cover types of interest by modifying Abdalla (1994) and Lawan (1996) and by drawing from FAO-Africover (2007). This was followed by adopting a systematic unaligned sampling procedure. Fifty sample squares (1km^2 in every ten km square) were selected.

From April to July 2006 the field survey was conducted and all the 50 samples were surveyed. Getting to the location of the sample square was the most difficult aspect of the field survey. Not all of the land covers listed in the initial classification were encountered in field, for example, none of the crop cultivated during the dry season, the marshy land cover types or the dumb palm were encountered. However two new land covers were judged to have covered a mapable area and possible spectrally separation was identified. The field work mapping was digitised.

The field survey was considered successful because all the sample squares were visited and the survey of the squares was undertaken without any problem, with the features identifiable in most situations.

Chapter 3 The Classification of the NigeriaSat-1 Image

3.1 Introduction

The fundamental issue considered in this chapter is how well can NigeriaSat-1 data be classified into the thirteen classes encountered during the field survey. In other words, is a land cover map produced by the classification of the NigeriaSat-1 image for these classes possible or accurate? To answer the question, spectral signatures were generated for the 13 classes. The histogram of the classes and their separability were examined to identify the likely success of the classification. The spectral signatures were then used to classify the NigeriaSat-1 image. The accuracy of the classification was computed and analysed prompting the need for improvement.

The improvement was first done by refining the spectral signatures through the application of the histogram analysis. The second approach was by enhancing the data through the addition of the Normalised Difference Vegetation Index (NDVI) of the image. The third was by applying majority filters on the classified image and finally by merging the classes into four land cover types.

3.2 The NigeriaSat-1 Image

The NigeriaSat-1 imagery is a product of a micro satellite weighing 98kg. It is a sun synchronous polar orbiting satellite which orbits at 686 km above the earth. It scans the earth using three wavebands: band 1 (near infrared), band 2 (red) and band 3 (green). The wavelengths included in each waveband are similar to Landsat ETM+ and TM (Table 3-1). It has a ground spatial resolution of approximately 32 m, (Akinyede et. al, 2004) an image size up to 600 km by 4,100 km, and a temporal resolution of 3-5 days (NASRDA, accessed 2008).

Table 3-1: The wavebands of NigeriaSat-1 compared to the equivalent Landsat TM and ETM+ bands

Band	NigeriaSat-1 (µm)	Landsat ETM+ (µm)	Landsat TM (µm)
Green	0.52 – 0.62	0.52 - 0.60	0.52 - 0.60
Red	0.63 – 0.69	0.63 - 0.69	0.63 - 0.69
Near Infrared	0.77 – 0.90	0.76 - 0.90	0.76 - 0.90

Source: NARSDA http://landsat.gsfc.nasa.gov/about/etm+.html, accessed 2008

Note: Only 3 of the bands of Landsat ETM+ and TM are shown here

The image used in this research was acquired on the 11th November 2005 at 09:13:18. DMC International imaging Ltd. supplied the image as three coregistered bands, which they term a Level 1R product (the complete image meta data is provided in Appendix A). Upon receipt, the image was co registered with the Landsat ETM+ image (see section 2.4.1). An at-sensor calibration was also undertaken in order to correct for the error in the detector system (Richards and Jia, 1999; Schowengerdt, 2007). A uniform atmospheric condition was assumed for the study, thus no radiometric correction to deal with the impact of the atmosphere was done. This was mainly because no atmospheric data was available to undertake such correction and since a post classification change analysis was used the impact of the atmosphere would be minimal (Coppin et al., 2004). The at-sensor calibration converted the digital number (DN) to radiance using Equation 3-1 (DMC, 2007) and was used in the computation of the Normalised Difference Vegetation Index (NDVI) for the NigeriaSat-1 image. To compute the radiance the rescaled-gain and the rescaled-bias were obtained from the image's meta data (Table 3-2).

$$RADIANCE = \frac{DN}{RESCALE\_GAIN} + RESCALE\_BIAS$$

Equation 3-1

Table 3-2: The NigeriaSat-1 image's scene *RESCALE_GAIN* and *RESCALE_BIAS* for computing at sensor radiation

Band	Gain (W/m^2/sr/m^{-6})	Bias (W/m^2/sr/m^{-6})
1	0.72	0.004
2	0.68	0.002
3	0.87	0.002

See Appendix A

3.3 Classification Methodology Background

The classification procedure can be divided into three stages: feature extraction, training and labelling (Schowengerdt, 2007). The objective of feature extraction is to reduce the dimension of the data to be classified and hence the cost of the classification (Richards and Jia, 1999); this procedure is optional (Schowengerdt, 2007). Feature extraction was not considered in this research because the NigeriaSat-1 sensor has only three wavebands which can be managed effectively with the computing facility available. Secondly it was the desire of this research to analyse the image with all its wavebands. The training stage entails determining certain parameters that define the boundary for the land cover classes. This research used the field survey result to help define the parameters of land cover classes from the NigeriaSat-1 image, that is, spectral signatures. The training stage was also used to examine the separability between the signatures, the objective of which was to determine prior to the classification the classes which may not be separable and needed to be merged.

In this research the separability analysis was used to analyse the separability of the 13 classes among the three wavebands of the image in order to partly answer whether the 13 classes could be separated. However, the classification would proceed with the 13 classes irrespective of the outcome, so that the classification result could be tested through error analysis. It was also reasoned that the classification of the 13 classes would also be used as the starting point for improvement should both the separability and classification results indicate the need for improvement.

The method of separability analysis is a statistical means of evaluating whether a pair of classes (hence their signatures) can be separated or not based on their probability density function. Whilst either divergence, Jeffries-Matusita (JM) distance or transform divergence could be used, the Jeffries-Matusita distance is the most appropriate algorithm for maximum likelihood classification (the classification method selected, as discussed below) (Richards and Jia, 1999).

The labelling for a supervised procedure could either label a pixel into a single class only, termed hard classification, or into more than one class, termed soft or fuzzy classification. The classification that fits into the traditional way thematic maps are used in general, that is, hard classification, was chosen. However, as will be shown later in the chapter and by others, the fuzzy method could be an alternative method especially where there are mixed pixels as experienced by Lawan (1996). The labelling algorithm either assumes a certain probability distribution function such as the normal distribution or not: the former is termed parametric which consists of methods such as maximum likelihood, Maholanobis and minimum distance; and the latter is termed nonparametric, which consists of parallelepiped and feature space. Although the nonparametric algorithms are robust, they do have overlap of classes and also sometimes fail to classify some pixels (Schowengerdt, 2007).

While the maximum likelihood (the Maholanobis and minimum distance being seen as its special cases) uses statistical parameters such as covariance to determine the likelihood of a pixel belonging to a certain class, its advantage is that it produces a better result when there are sufficient samples and they conform to a normal distribution. Where this conditions fails or a faster method is required the maximum distance could be better (Schowengerdt, 2007; Richards and Jia, 1999).

Another method that has become popular is artificial neural networks (ANNs). These work by self-training (Lillesand and Kiefer, 1999), with the advantages of learning complex patterns, generalisation in noisy environments, and works with different sources of knowledge (Mas and Flores, 2008). There are many claims that it produces better classification results than the maximum likelihood but this has been questioned by Wilkinson (2005) and Mas and Flores (2008).

The maximum likelihood method was selected as the main method of classification because it is the most accurate amongst the common classifiers, and even the special ones such as ANNs are not said to be significantly different. However, it will be seen later that other methods were incorporated in an effort to improve the classification accuracy.

The maximum likelihood method labels a pixel by using Equation 3-2 to compute D for all the land covers using their signatures. All parameters in the equation are obtained from the spectral signatures already generated, except X the value of the pixel to be to be labelled. The land cover signature that produces the least D provides the attribute for the pixel (Schowengerdt, 2007; Richard and Jia, 1999; Leica Geosystems Geospatial Imaging LLC, 2005).

$$D = \ln(p_{ic}) - [0.5\ln(|C_c|)] - [0.5(X - M_c)^T (C_c^{-1})(X - M_c)] \qquad \textbf{Equation 3-2}$$

Where:

D = weighted distance (likelihood)

c = a particular class

X = a candidate pixel

M_c = the mean vector of the sample of class *c*

P_{ic} = percent probability that any candidate pixel is a member of class *c* (defaults to 1.0, or is entered from *a priori* knowledge)

C_c = the covariance matrix of the pixels in the sample of class *c*

$|C_c|$ = determinant of C_c

ln = natural logarithm function

T = transposition function

The result of the classification is a thematic map or a summary table of the pixel count of the land cover classes. Both were used as input for analysing change detection.

The accuracy of the classification usually tests whether the result should be accepted or not and thus provides confidence in the overall land cover mapping (Richards and Jia, 1999).

Two questions need answering at this point: what method of classification accuracy assessment should be used and what threshold would indicate whether a map is credible or not. One of the prominent ways to assess the accuracy of a classification is to compare a classified image against reference data using a confusion matrix (Congalton et. al., 1983, Congalton, 1991). In this method the value of a classified pixel (or block of pixels or polygon) is compared to the corresponding reference pixel. Since only sample points or polygons are used, their selection should meet the condition of being random and independent of the pixels used earlier to train the classification.

The comparison is often presented in tabular form (Table 3-3) and called the confusion or error matrix. The diagonal entries are the correctly classified pixels, based on the assumption that the reference data are the correct values and the pixels of the classified image agree with the reference, and the classification is therefore correct at that point. This also means that the off diagonal elements are wrongly classified. These wrongly classified elements are often considered from two perspectives: commission errors and omission errors. For example, a_{12} (Table3-3) is a commission error in the classification of class 1 but an omission error in the correct classification of class 2. The correctly classified pixels within a class compared to its column total (i.e. reference data) gives the producer accuracy (Equation 3-3) while compared against its row total gives the user accuracy (Equation 3-4). These two accuracy measures provide an indication of how well a class was classified. The overall accuracy (Equation 3-5) is the proportion of correctly classified pixels compared to all of the pixels used (Congalton and Green, 1999).

The Kappa statistic is another measure of classification accuracy that can be drawn from the confusion matrix. It measures how well the classified data agrees with the reference data and removes agreement due to chance; this is expressed in Equation 3-6 and can be expressed as Equation 3-7 when applied to the confusion matrix (Congalton and Green, 1999; Pontius 2000; Lillesand and Kiefer, 1999). Its ability to measure the level of agreement has made it a tool to compare results of several classification procedures using the standardised normal distribution, expressed in Equation 3-8 (Congalton and Green, 1999).

Its ability to remove chance agreement and be used to measure significant differences between confusion matrices makes it the second most used measure of agreement and the most popular means of comparing confusion matrices (Gomez et al., 2008). It has been argued (Foody, 2002; Foody, 2006; Pontius, 2000) that kappa statistics are not the only means of comparison based on confusion matrices nor is any individual measure superior amongst them or the most appropriate (Foody, 2002; Foody, 2006; Pontius 2000; Leeuw et al., 2006).

Kappa has been criticized as a means of comparison because one of the basic assumptions, that is, the matrices being compared should be independent, is often not true in many remote sensing applications (Foody, 2004). One effort to correct the problem was to attempt to remove the covariance between two matrices (Equation 3-8) (Donner et al., 2000). There seems to be no enthusiasm in pursing the Donner et al. (2000) approach as there is no example of its usage in the remote sensing literature reviewed. If the dependent confusion matrices must be accounted for in using kappa statistics, then there is a need to research the application of such in remote sensing applications. Meanwhile if kappa must be used without removing the covariance, as in Donner et al. (2000), it is assumed that it will be meaningful only if the estimate of z is obviously too large or too small, that is, the effect of the covariance will not affect the decision taken. Foody (2004) and Leeuw (2006) suggest the use of the McNemar, Chi-square randomisation as an alternative to the kappa rather than seeking to improve it.

To apply the McNemar test, a new 2x2 contingency matrix (Table 3-4) was required, derived from the two confusion matrices in terms of correctly and incorrectly classified pixels. The test could then be conducted based on the standardised normal distribution (Equation 3- 10) or chi-square (Equation 3-11).

Table 3-3 Illustration of a confusion matrix

				Reference:		
	Class1	**Class 2**	**…**	**Class N**	**Row Total**	**User Accuracy%**
Classified						
Class 1	a_{11}	a_{12}	…	a_{1N}	a_{1+}	a_{11}/a_{1+}
Class 2	a_{21}	a_{22}	…	a_{2N}	a_{2+}	a_{22}/a_{2+}
⋮	⋮	⋮	…	⋮	⋮	⋮
Class N	a_{N1}	a_{N2}	…	a_{NN}	a_{N+}	a_{NN}/a_{N+}
Column Total	A_{+1}	a_{+2}	…	a_{+N}	a_{++}	
Producer accuracy%	A_{11}/a_{+1}	a_{22}/a_{+2}	…	a_{NN}/a_{+N}		

$$\text{Producer accuracy} = \frac{n_{jj}}{n_{+j}}$$ **Equation 3-3**

$$\text{User accuracy} = \frac{n_{ii}}{n_{i+}}$$ **Equation 3-4**

$$\text{Overall accuracy} = \frac{\sum_{i=1}^{k} n_{ii}}{n}$$ **Equation 3-5**

$$Kappa = \frac{Observed\_accuracy - chance\_agreement}{1 - chance\_agreement}$$

Equation 3-6

$$K = \frac{\sum_{i=1}^{k} n_{ii} - \sum n_{i+}n_{+i}}{n^2 - \sum_{i=1}^{k} n_{i+1}n_{+i}}$$ **Equation 3-7**

$$Z = \frac{|K_1 - K_2|}{\sqrt{\sigma_{K_1}^{\ 2} + \sigma_{K_2}^{\ 2}}}$$ **Equation 3-8**

$$Z = \frac{| K_1 - K_2 |}{\sqrt{\sigma_{K_1}{}^2 + \sigma_{K_2}{}^2 - 2\sigma_{K_1K_2}}}$$ **Equation 3-9**

Table 3-4 Illustration of a contingency matrix for comparing two classifications using the McNemar test

	Classification 2		
	Correct	**Incorrect**	**Total**
Classification 1			
Correct	**a**	**b**	**a+b**
Incorrect	**c**	**d**	**c+d**
Total	**a+c**	**b+d**	

$$Z = \frac{b - c}{\sqrt{b + c}}$$ **Equation** 3-10

$$\chi^2 = \frac{(b - c)^2}{b + c}$$ **Equation** 3-11

Where

a = the pixels that are correct in both classification

b = the pixels that are correct in classification 1 but incorrect in classification 2

c = the pixels that are correct in classification 2 but incorrect in classification 1

d = the pixels that are incorrect in both classification.

Kappa statistics and a Chi-square test were used. The kappa statistic tests whether there is agreement between two confusion matrices, while the Chi-square tests whether the relationship between the correct and the incorrect pixels in the two classifications are the same. The McNemar test was not conducted because one of the confusion matrices was different in sample size.

The answer as to which accuracy assessment is credible can be considered in two ways: the first is by the measurement of accuracy, for example, the overall, or kappa statistics, and the second by the demand of the users (Foody, 2006). Since there were no demands on this research, the research used the overall accuracy. Foody (2006) argues that there is no universal agreement on an acceptable measure of accuracy, and Wilkinson (2005) showed from fifteen years of reported results of classifications that the mean overall classification accuracy was 76.19% with a standard deviation of 15.59. This research aimed to achieve the mean and lie within the standard deviation stated above. This accuracy would make it comparable to Lawan (1996) who reported an overall accuracy between 62% and 67%.

3.4 Extraction of Training Pixels and the Spectral Analysis

The field data acquired were used to select pixels in relation to land cover types and the pixels were then used to generate spectral signatures for each of the land covers. The pixels selected for the training were then analysed to provide the response pattern of each of the spectral signatures and their relationship with each other prior to the classification. The results can be analysed graphically or quantitatively. The graphical analysis could be a one dimensional coincidental plot or a histogram; both are considered here and in addition to the quantitative analysis. The analyses were also used to refine the spectral classes (Swain, 1978; Lillesand and Kiefer, 1999)

3.4.1 Generation of spectral signatures

In order to generate spectral signatures for each land cover from: the field data (chapter 2), the NigeriaSat-1 image together with systematically arranged floating points (created as a template to be used severally, designed based on the systematically aligned sampling method, see chapter 2) were set up in the Erdas Imagine’s viewer as layers (Figure 3-1). The signatures for the each land cover were generated one at a time. For example, in generating the signature for bare ground: the floating points were laid over all of the 50 field survey sample squares, then all points that did not correspond to bare ground were eliminated. The remaining points were used in the Erdas Imagine’s Signature Editor to merge the point into the class’s spectral signature. The signature consisted of the parameters needed to discriminate the class such as the mean and the covariance (Equation 3-2).

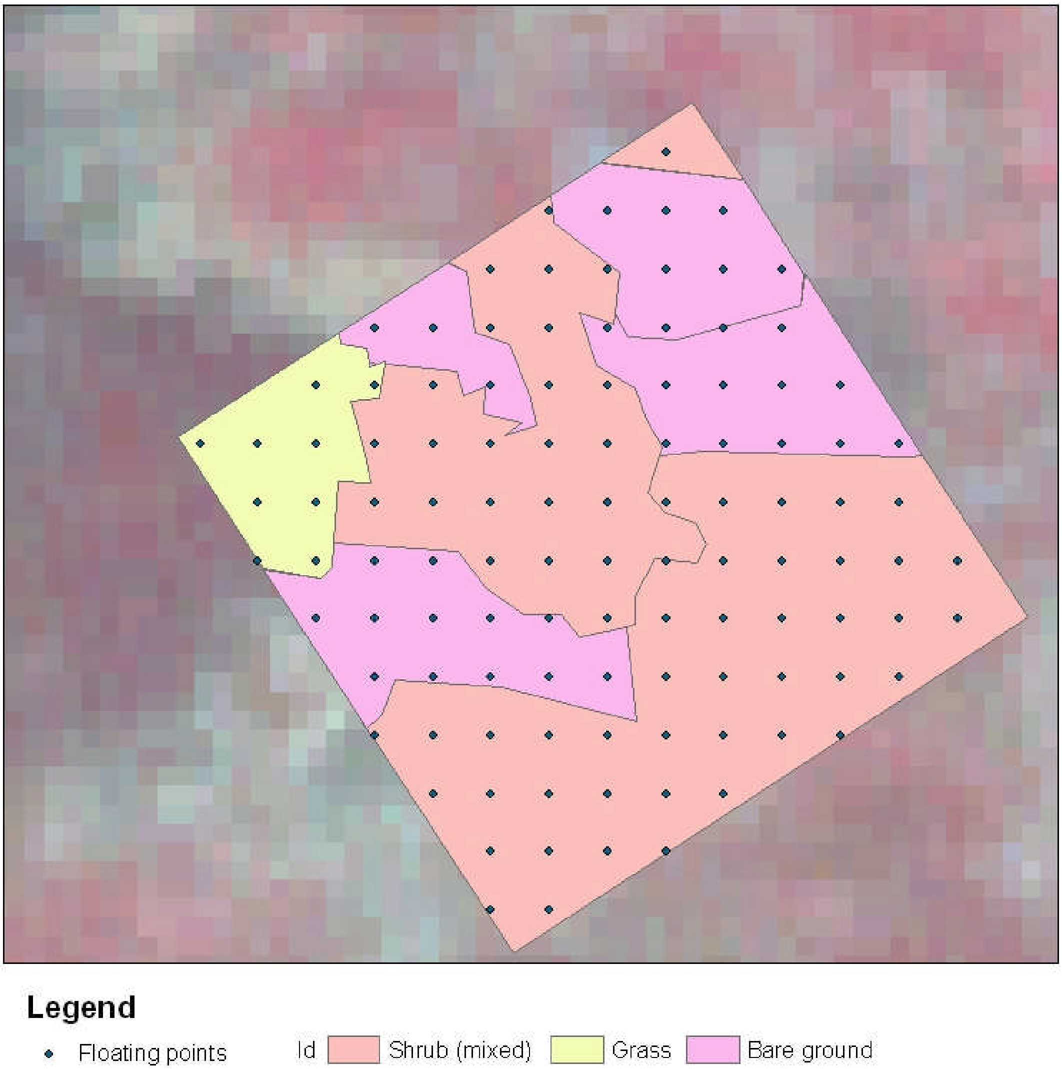


Figure 3-1: An illustration of the arrangement of the systematically arranged floating points laid over field data indicating the location of land covers and the NigeriaSat-1 image from which the characteristics of the pixel belonging to a land cover were derived.

3.4.2 Coincident spectral plot analysis of the spectral signature

A coincident spectral plot provides a means of understanding how the land cover classes are likely to behave in the course of classification. This is a one dimensional view representing the land covers using the means and standard deviation in order to visualise the spectral overlap of each land cover (Lillesand and Kiefer, 1999).

Figure 3-2 shows the coincident spectral plot for the spectral signatures derived from the NigeriaSat-1 image. In Figure 3-2, only short tree (Kwargo, *Bauhinia rusfenscene*) had an exclusively different range from orchard, shrub (sabara, *Guiera senegalense*) and bare ground in the infrared waveband; the short tree (Kwargo, *Bauhinia rusfenscene*) was also separable from bare ground in the red waveband but there is no such separation in the green waveband. The overall patterns of the relationships between the land covers indicated a general likelihood of difficulty in separating the land cover classes due to the overlapping spectral ranges within and across wavebands.

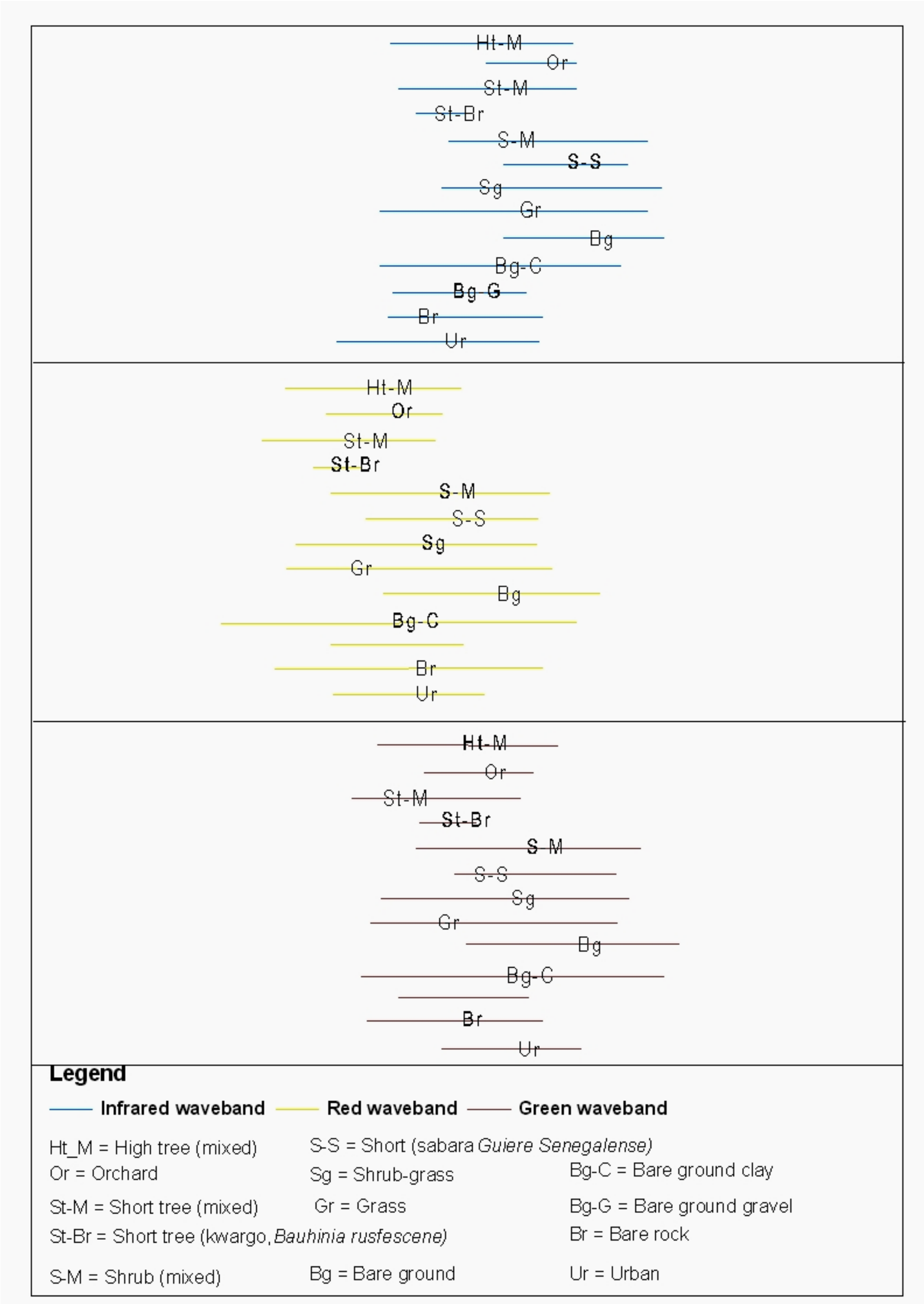


Figure 3-2: Coincident spectral plot of the thirteen land cover types

3.4.3 Histogram analysis of spectral signatures

Histogram analysis was another form of graphical analysis undertaken, whose purpose was to provide an understanding of the coincidence of the land covers in two dimensions and to evaluate whether the probability density function of each of the land covers conformed to the assumptions implicit in the supervised classification, specifically maximum likelihood (Swain 1978; Richards and Jia, 1999). To achieve the first, the histograms of the land covers are presented together according to the three bands of the NigeriaSat-1 (Figures 3-3, 3-4 and 3-5). The second purpose was achieved by plotting each land cover separately (Figure 3-6).

There were no complete separations between the land covers in all three wavebands (Figures 3-3, 3-4 and 3-5). The short tree (mixed) and shrub (mixed) do indicate some low level separation although there is a high degree of overlap.

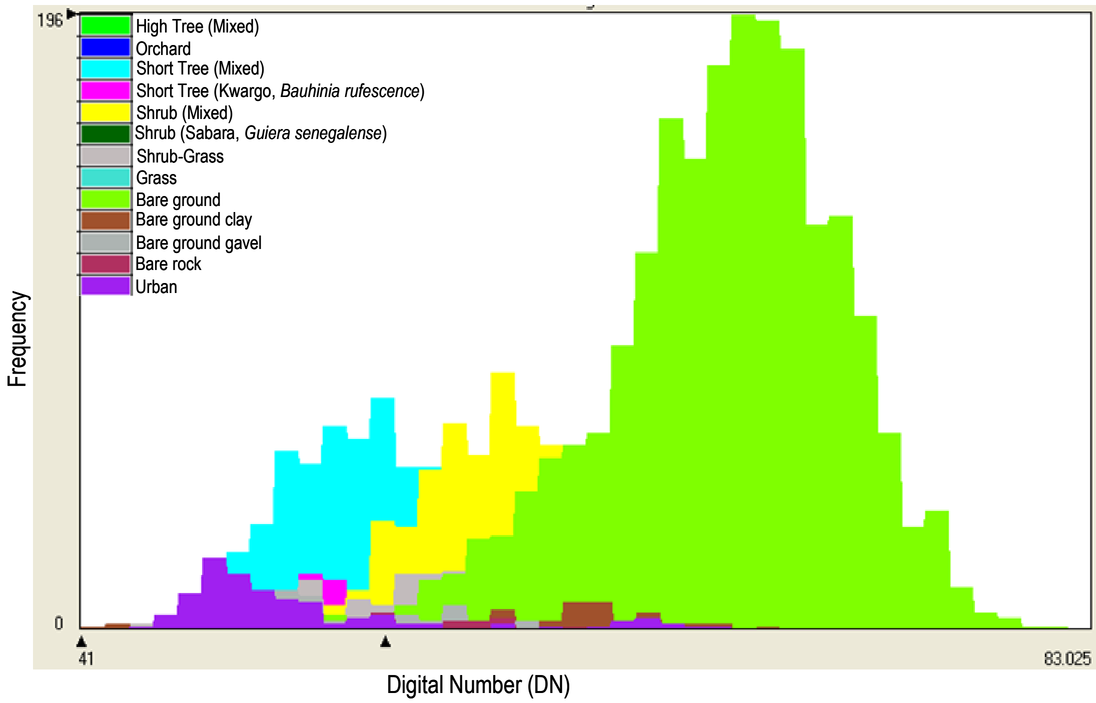


Figure 3-3: Coincident histogram of the 13 land covers derived from the infrared waveband of the NigeriaSat-1 image illustrating the difficulty in separation

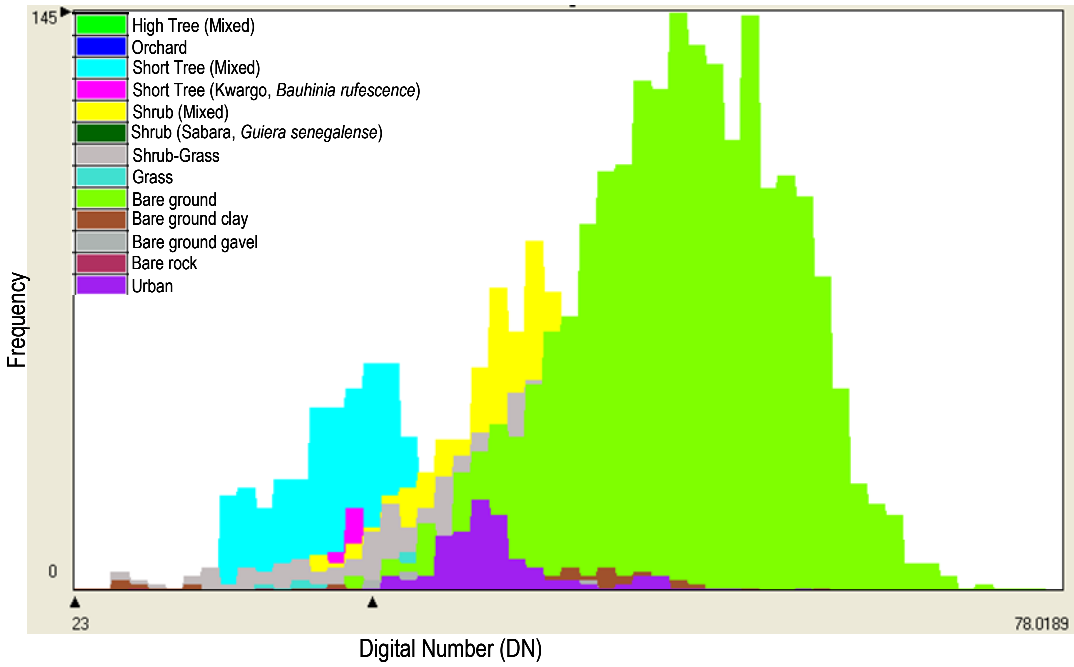


Figure 3-4: Coincident histogram of the 13 land covers derived from the red waveband of the NigeriaSat-1 image illustrating the difficulty in separation

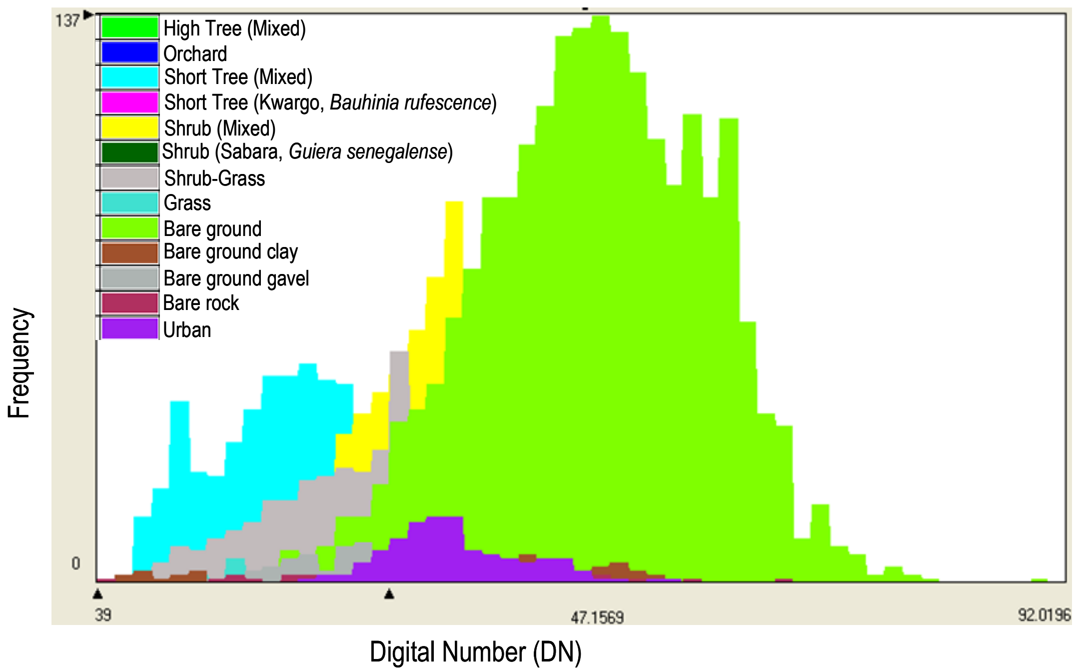


Figure 3-5: Coincident histogram of the 13 land covers derived from the green waveband of the NigeriaSat-1 image illustrating the difficulty in separation

The plot of the histogram of the individual land covers in the infrared waveband is shown in Figure 3-6 (selected to illustrate the analysis). It was obvious that there were many land covers with multimodal probability density functions, especially the high tree (mixed), shrub (mixed), grass, and bare ground clay. Some were too widely spread to fit a particular form (e.g. shrub grass). The bare ground tended to give the normal distribution form in general, however, there were chances that the few peaks noticeable would make it multimodal.

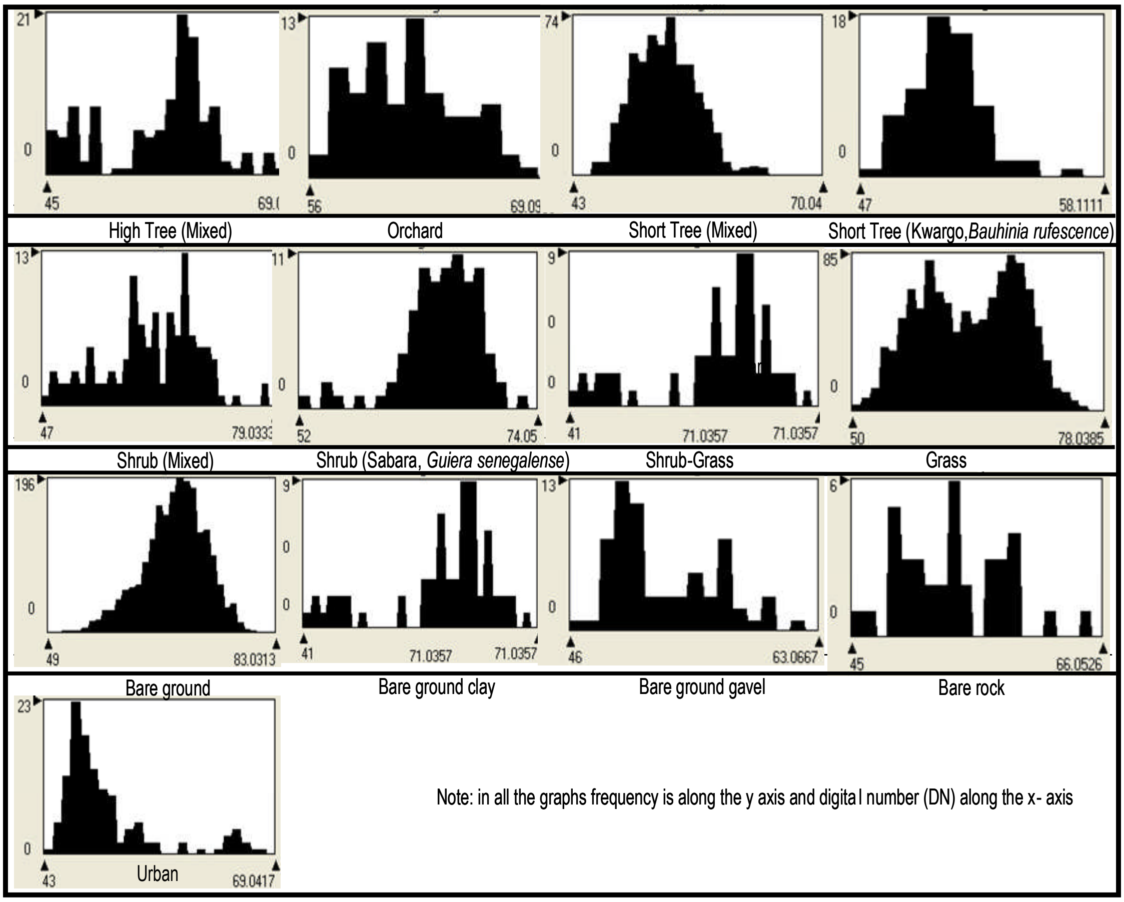


Figure 3-6: Individual histograms of the land covers in the infrared waveband.

3.4.4 Separability analysis

There were 78 pairs of combinations of the 13 classes and the JM distance was computed for each pair. The results were categorised arbitrarily following the example of Jose et al. (2004) into three: those with JM distances of 1200 to 1414 were considered to have high separability, those with JM distances between 1000 and 1200 as good separability and those with JM distances less than 1000 as poor separability. Using the above criteria it was found that only 23 of the 78, that is, 30% of combinations, were separable in at least one band as shown in Table 3-5. Of the 23 separable combinations, 13 were separable in only one band, 5 in two of the bands and 5 in all three bands. The 55 other combinations that were not separable indicated that most of the land cover classes would be poorly classified. Table 3-6 relates the wavebands of the NigeriaSat-1 image to the type of separability to indicate which waveband would produce a better separability in the classification. It appeared from Table3-6 that the infrared waveband had a greater proportion of high separability and hence it was thought that it would produce a better separation between the classes.

Table 3-5: Separability of the 13 land cover classes using the Jeffries-Matusita (JM) distance

Classes	Wave band No. of NigeriaSat-1	High Tree (Mixed)	Orchard	Short Tree (Mixed)	Short Tree (Kwargo, *Bauhinia rufescence*;	Shrub (Sabara, *Guiera senegalense*)	Bare Ground
Short Tree (Mixed)	**1**		**G**				
Short Tree (Kwargo, *Bauhinia rufescence*)	**1**		**H**				
	2		**G**				
Shrub (Mixed)	**1**				**H**		
	2				**G**		
	3				**G**		
Shrub (Sabara, *Guiera senegalense*)	**1**			**H**	**H**		
	2			**G**	**H**		
	3			**G**	**G**		
Shrub-grass	**1**				**G**		
	2				**G**		
Grass	**1**				**G**		
	2				**G**		
	2				**G**		
	3						**G**
	2				**G**		
	3				**G**		
Bare ground	**1**			**H**	**H**		
	2	**G**	**G**	**G**	**H**		
	3		**G**	**G**	**H**		
Bare ground clay	**1**				**G**		
Bare ground gravel	**1**		**G**			**H**	**H**
	2				**G**		
	3						**G**
Bare rock	**1**					**G**	**G**
	2				**G**		
Urban	**1**		**G**			**G**	**G**
	2				**G**		
	3				**G**		

Note: High separability (H) = JM > 1200, good separability (G) = 1000 < JM > 1200, and JM < 1000 poor separability is not represented.

Table 3-6 Summary of the overall type of separability according to percentage occurrence within each waveband

	Type of separability		
	Poor separability	Good separability	High separability
Spectral waveband	%	%	%
Band 1 (Infrared)	76.9	11.5	11.5
Band 2 (Red)	83.3	14.1	2.6
Band 3 (Green)	89.7	9.0	1.3

3.5 Classification of the thirteen classes

Classification was undertaken for the thirteen classes using the maximum likelihood method resulting in a thematic map shown in Figure 3-7. The image was produced at a scale of about 1:500,000. At such a small scale it is difficult to analyse the classification, however when enlarged to approximately 1:50,000 (Figure 3-8) it is possible to see patterns of major land covers such as short tree and bare ground. Figure 3-8 also provides a visual comparison of the classified image with the reference data. Figures 3-8 C and H, D, G and E, and I, respectively, show examples where short tree (mixed), short tree (Kwargo, *Bauhinia rufescence*), bare ground and urban matched well between the reference and classified image, and Figures 3-8 C and F illustrate cases of mismatch between bare ground and grass..

A more objective way to assess the classification was to use the confusion matrix. Thus, 3448 randomly located pixels were selected independently of those used in the generation of the spectral signatures and were compared to the field reference data. The result is presented in Table 3-7 and shows an overall accuracy of 37%. This is a poor classification, and confirms the results from the separability analysis.

The producer and user accuracies are summarised in Table 3-9, where they are arbitrarily divided into three levels of accuracy: those with 70% or greater signifying high accuracy, those with more than 50% but less than 70% signifying moderate accuracy and those with less than 50% considered to be poor. The number of reference pixels and the classified data was also considered, that is, those with more than 50 reference pixels and those also with less than 50 pixels. This value was chosen arbitrarily, to indicate the categories whose percentages arose from small numbers of reference pixels, thus any chance of misclassification would have greater impact and hence distort the result,. From table 3-9, there was no land cover with high producer and user accuracy, however, short tree (Mixed), short tree (kwargo, *Bauhinia rufescence*) and bare ground have either high producer or user accuracies.

An analysis of the misclassification, that is, pixels classified into a land cover other than indicated by the reference data in Table 3-7, shows that with the exception of short tree (Mixed) and short tree (kwargo, *Bauhinia rufescence*) all the other classes have more than 10% of their area confused with bare ground, and the worst case was the shrub (mixed) which had 60%. A similar characteristic could be seen with the shrub (mixed), short tree (Mixed) where a substantial percentage of the classified land cover actually belonged to another class in the reference dataset.

The shrub grass group, that is, shrub (mixed), shrub (sabara, *Guiera senegalense*), shrub-grass and grass, have lower than 10% producer accuracies as a group than other classes except the Shrub (Sabara, *Guiera senegalense*) class and lower user accuracies especially the shrub (sabara, *Guiera senegalense*) and grass classes which had less than 5% user accuracies. One could suspect that the group was the cause of the poor classification overall, and this could raise the question of: what is the effect of the classification of the shrub on the overall accuracy and on the classification of the other land covers? This was tested by removing the group from the classification and assuming that all the other relationships and conditions remained as they were. Thus a new confusion matrix was computed (Table 3-9) by simply removing the elements of the shrub grass group from Table 3-7.

By removing the shrub grass group the overall accuracy rose to 70%. All of the land covers had accuracies of more than 60% except bare rock. The producer accuracies also increased in all cases.

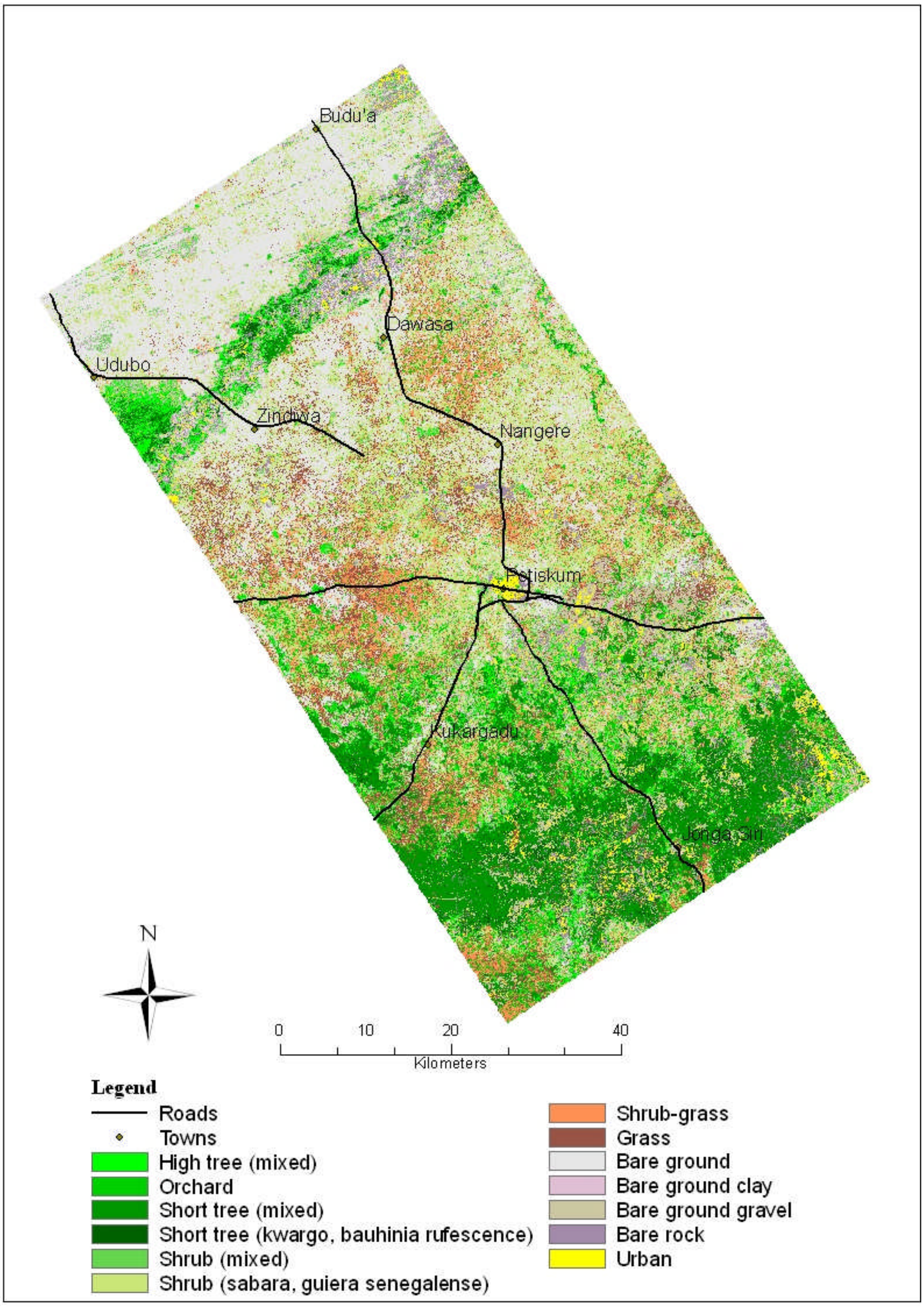


Figure 3-7: Classification of the NigeriaSat-1 image into 13 land cover categories

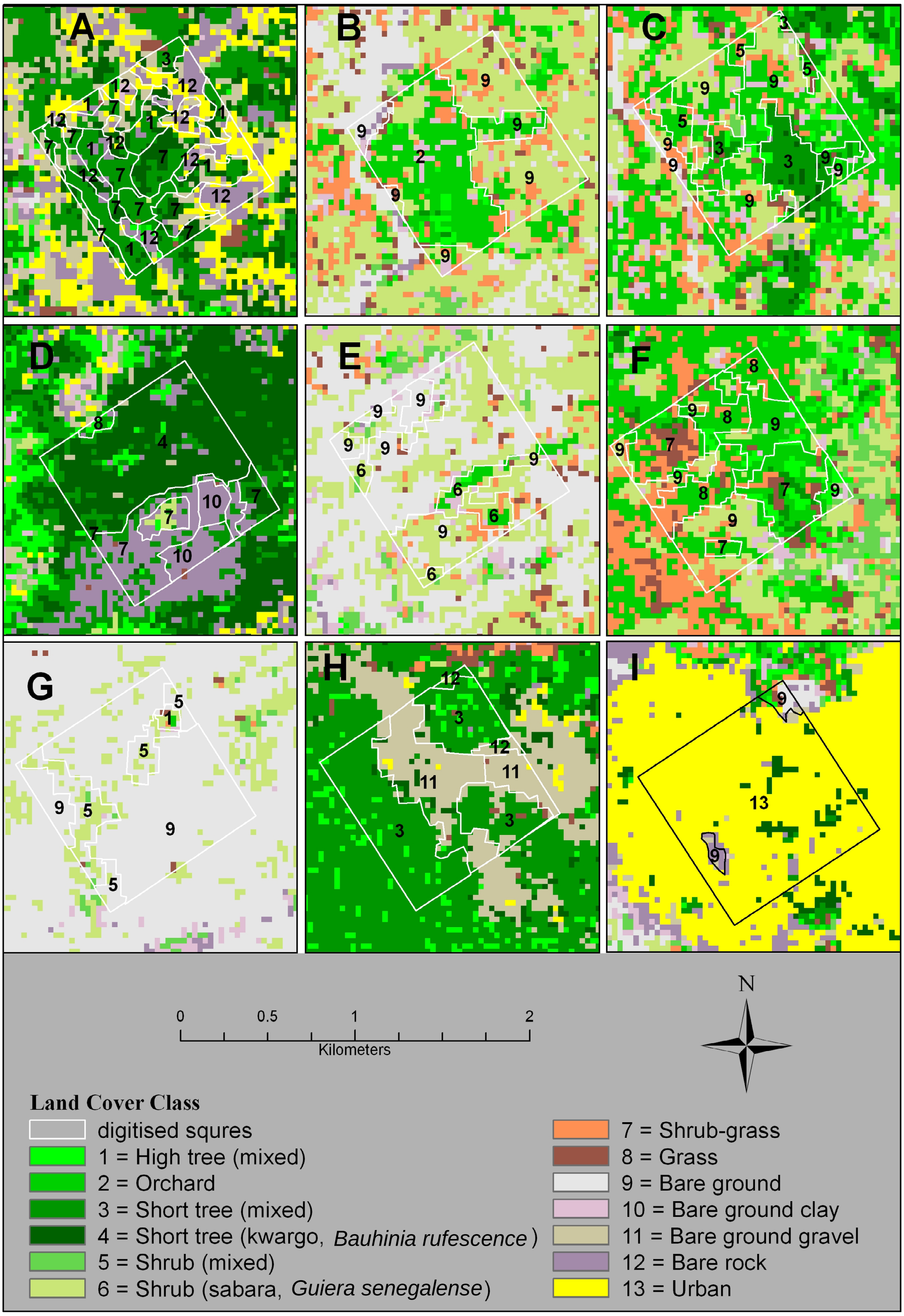


Figure 3-8: Larger scale images of parts of the classified NigeriaSat-1 image with thirteen classes, overlaid with digitised sample square polygons from the field survey. The number indicates the field survey classes.

Table 3-7: Confusion matrix of the NigeriaSat-1 image classified into thirteen land cover classes

		REFERENCE														
	Class name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**Row Total**	**User Accuracy (%)**
CLASSIFIED	1. High tree (mixed)	44	1	66		69		17	1	23	5	3			229	19.2
	2. Orchard	13	52	10		122	5	128	20	94	4				448	11.6
	3. Short tree (Mixed)	7		273		46		14	15	9	1	1	1		367	74.4
	4. Short tree (Kwargo, *Bauhinia rufescence*)	1		23	42	1		3	1				2	1	74	56.8
	5. Shrub (mixed)	2		2		8		4		25	1				42	19.1
	6. Shrub (Sabara, Guiera *senegalense*)	1	2	6		170	27	133	12	330	1			11	693	3.90
	7. Shrub-grass					4		7		6					17	41.2
	8. Grass		1	7		29		41	7	68		1			154	4.6
	9. Bare ground	1		1		126	10	84	6	682	1			5	916	74.5
	10. Bare ground clay	3		20	1	37		16		78	25				180	13.9
	11. Bare ground gravel	1	1	50		66	3	14	4	21		24	2		186	12.9
	12. Bare rock	1		5		13		2	2	21	1		7	1	53	13.2
	13. Urban	1				12		1		11	1		3	60	89	67.4
	Column Total	75	57	463	43	703	45	464	68	1368	40	29	15	78	3448	
	Producer Accuracy (%)	58.7	91.2	59.0	97.7	1.14	60	1.51	10.3	49.9	62.5	82.8	46.7	76.9		
Overall Accuracy (%)		36.5														
Kappa (%)		26.8														
Variance (kappa)		7.7E-5														

Note: The numbers in the class name row relate to the class name as given in the class name column.

Table 3-8: The distribution of the producer and user accuracies from the classification of the NigeriaSat-1 image into thirteen land cover classes

	Producer accuracy		User accuracy	
Accuracy level	Reference pixel > 50	Reference pixel <50	Reference pixels > 50	Reference pixels < 50
> 70%	Orchard, Urban	Short tree (Kwargo, *Bauhinia rufescence*), Bare ground gravel	Short tree (Mixed) Bare ground	
< 70% but >50%	High tree (mixed), Short tree (Mixed), Bare ground	Bare ground clay, Shrub (Sabara, Guiera *senegalense*)	Urban, Short tree (Kwargo, *Bauhinia rufescence*)	
<50%	Shrub (mixed), Shrub grass, Grass	Bare rock	High tree (mixed), Orchard, Shrub (Sabara, Guiera *senegalense*), Grass, Bare ground clay, Bare ground gravel, Bare rock	Shrub (mixed), Shrub grass

Table 3-9: Confusion matrix of the NigeriaSat-1 image classified into thirteen land cover classes without the elements of the shrub grass group

		REFERENCE										
	Class name	1	2	3	4	9	10	11	12	13	Row Total	User Accuracy (%)
CLASSIFIED	1. High tree (mixed)	44	1	66		23	5	3			142	30.99
	2. Orchard	13	52	10		94	4				173	30.06
	3. Short tree (Mixed)	7		273		9	1	1	1		292	93.49
	4. Short tree (Kwargo, *Bauhinia rufescence*)	1		23	42				2	1	69	60.87
	9. Bare ground	1		1		682	1			5	690	98.84
	10. Bare ground clay	3		20	1	78	25				127	19.69
	11. Bare ground gravel	1	1	50		21		24	2		99	24.24
	12. Bare rock	1		5		21	1		7	1	36	19.44
	13. Urban	1				11	1		3	60	76	78.95
	Column Total	72	54	448	43	939	38	28	15	67	1704	
	Producer Accuracy (%)	61.1	96.3	60.9	97.7	72.6	65.8	85.7	46.7	89.6		
Overall Accuracy (%)		70.95										
Kappa (%)		59.63										
Variance (kappa)		0.0002										

3.6 Improvement of the Classification

The evaluation of the spectral signatures and the result of the analysis of the confusion matrix of the classification indicated some possible reasons for the poor classification. The reasons included: the lack of separability between many of the classes and the multimodality of some of the land covers. These thus formed the basis for identifying methods to improve the classification. The first method tested was to refine the spectral signatures with the aim of removing multimodality and extremely low separability. The second method tested enhancing the image by adding NDVI data to improve the discrimination between the classes. The third method was to apply a majority filter in order to modify the classified image and possibly eliminate the impact of mixed pixels. The fourth approach merged the land cover classes into larger categories.

3.6.1 Refinement of spectral signatures

In order to achieve the spectral signature refinement mentioned above, the histogram analysis was used to separate the spectral signatures into unimodal classes, which were subsequently analysed for separability. Thus from the image histogram analysis (section 3.4.3), classes exhibiting multimodality were reprocessed using the number of peaks in the distribution to subdivide the class using an unsupervised classification method (ISODATA algorithm). This process produced 41 class signatures. The signatures were then subjected to separability analysis (similar to section 3.4.4) and classes that had very poor separability within a major grouping, that is, level 1 of the classification scheme (Table 2.2), for example, tree, were merged because they belonged to the same category by name and were not separable spectrally. This action then overrode the histogram separation. In the signatures which were not separable across categories, for example, shrub and bare ground, the signatures were eliminated. These signatures were assumed to be made up of mixed pixels of the two categories appearing in both categories. For example, if the histogram analysis produced 3 types of tree, say tree-a, tree-b and tree-c as well as 3 types of shrub, say shrub-a, shrub-b and shrub-c and suppose tree-c and shrub-b were not separable, the assumption was that both were a mixture of the two. Thus by eliminating the two signatures the others that remained would be sufficient for the classification. This process resulted in 11 spectral signatures. By this process the orchard and shrub (sabara, *Guiera senegalense*) classes were eliminated.

The classification with the new 11 spectral signatures produced an overall accuracy of 40% (Table 3-10). This was still poor by the standard of the accuracies achieved by Lawan (1996), for example. The overall accuracy was not significantly different compared to the overall accuracy from the first classification (Table 3-19). There were, however, some changes in the producer and user accuracies and consequently the misclassification of pixels. For example, there was a reduction of 8% and 11% in the producer and 26% and 40% in the user accuracies of both the short tree (kwargo, *Bauhinia rufescence*) and bare rock, respectively. The shrub grass and the urban classes did improve their producer accuracies by 28% and 25%, respectively.

3.6.2 Image enhancement using NDVI

The Normalised Difference Vegetation Index (NDVI) is widely used as a means of measuring various vegetation related properties (Jensen, 2000; Sannier, 2000; Wagenseil and Samimi, 2006). The separability analysis indicated that the infrared and red wavebands were better at separating land covers than the green waveband. Thus it was thought that by adding the NDVI to the original image, the discrimination between the vegetated areas and the non vegetated would be enhanced. Thus an NDVI was computed by using the infrared and the red band of the NigeriaSat-1 image (Equation 3-12). The NDVI was then added as a fourth layer and hence the classification was conducted with a new definition of spectral signatures based on the 4 bands.

$$NDVI = \frac{Near\_Infrared - \mathrm{Re}\,d}{Near\_Infrared + \mathrm{Re}\,d} \qquad \textbf{Equation 3-12}$$

This procedure produced an overall accuracy of 42% (Table 3-11), which was not significantly different to the previous classifications (Table 3-19). As with the refinement procedure, the producer and user accuracies are different from the original classification. In general, the producer accuracies decreased while the user accuracies improved. For example, orchard, short tree (kwargo, *Bauhinia rufescence*), and shrub-grass decreased by more than 50%, the grass and the bare rock increased by more than 30% in the producer accuracies compared to the original classification. The user accuracies on the other hand had short tree (Kwargo, *Bauhinia rufescence*), urban and orchard increasing by 43%, 11% and 29%, respectively, and the shrub grass decreased by 18%.

Table 3-10: Confusion matrix of the NigeriaSat-1 image, classified into eleven land cover classes based on refined spectral signatures.

		REFERENCE												
		1	2	3	4	5	6	7	8	9	10	11	Row Total	User Accuracy (%)
CLASSIFIED	1. High tree (mixed)	43	96	2	87	25	3	25	2	5	1		289	14.9
	2. Short tree (mixed)	5	192	3	19	8	16	3	1	1	1		249	77.1
	3. Short tree (kwargo, Bauhinia rufescence)	1	24	31	2	3				1	1	1	64	48.4
	4. Shrub (mixed)	5	9		87	60	2	161	4	1		7	336	25.9
	5. Shrub-grass	5	13		182	217	20	222	4			1	664	32.7
	6. Grass	5	21		82	71	19	187		1		2	388	4.9
	7. Bare ground		1		129	88	6	661	1			5	891	74.2
	8. Bare ground clay	6	31	4	54	17		93	24		2	2	233	10.3
	9. Bare ground gravel	4	61	3	28	10	2	4		19	9		140	13.6
	10. Bare rock		14		33	9		11	4	1	1	6	79	1.3
	11. Urban	1	1			1		1				54	58	93.1
	Column total	75	463	43	703	509	68	1368	40	29	15	78	3391	
	Producer accuracy (%)	57.3	41.5	72.1	12.4	42.6	27.9	48.3	60.0	65.5	6.7	69.2		
Overall accuracy (%)		39.7												
Kappa (%)		27.2												
Variance (Kappa)		9.6E-5												

Table 3-11: Confusion matrix of the NigeriaSat-1 image plus NDVI classified into thirteen land cover classes

		REFERENCE														
		1	2	3	4	5	6	7	8	9	10	11	12	13	Row total	User accuracy (%)
CLASSIFIED	1. High tree (mixed)	44	2	115	12	76		19	2	15	5	4			294	15.0
	2. Orchard	0	20	1		18	2	13	2	28	1				85	23.5
	3. Short tree (mixed)	4		230	1	30		10	12	4	1	1			293	78.5
	4. Short tree (kwargo, *Bauhinia rufescence*)				20										20	100.
	5. Shrub (mixed)	12	7	14		87	3	30	4	108	2			3	270	32.2
	6. Shrub (sabara, *Guiera senegalense*)		1	1		20	3	10	0	20					55	5.5
	7. Shrub-grass		2	4		28		23	1	41					99	23.2
	8. Grass	4	25	23		147	12	190	35	209		1		2	648	5.4
	9. Bare ground	1		1		205	23	136	8	885	4			11	1274	69.5
	10. Bare ground clay	1		16	1	27		15		22	24				106	22.6
	11. Bare ground gravel			37	0	35	2	9	2	7		21	2		115	18.3
	12. Bare rock	9		21	9	29		9	2	29	3	2	12	6	131	9.2
	13. Urban												1	56	58	96.6
	Column total	75	57	463	43	703	45	464	68	1368	40	29	15	78	3448	
	Producer accuracy (%)	58.7	35.1	49.7	46.5	12.4	6.7	5.0	51.5	64.7	60.0	72.4	80.0	71.8		

Overall accuracy (%) 42.34

Kappa (%) 29.23

Variance (kappa) 8.8E-5

3.6.3 Application of majority filters

The majority filter was applied as a means of generalising the classified image and for removing any 'salt and pepper' effects in the presentation of the thematic maps (Lillesand and Kiefer; 1999). In this method, the reference data with which the classified image was being compared to was created from mapping units that were greater than one pixel in size. The classification was carried out on a per pixel basis. Therefore by applying a majority kernel the pixels within a defined window were transformed to have the same value as the majority pixel value. The possibility of this discrepancy occurring between the reference data and the classified data was more likely in this study because of the sparse vegetation. This process was also expected to reduce the effects that could possibly arise from image misregistration (Lillesand and Kiefer, 1999; Lu and Weng, 2007).

Three kinds of filter (3x3, 5x5 and 7x7) were applied to the three classification methods already conducted, with the view of finding which produced the better overall accuracy. The three types were selected so that they did not overly transform the neighbourhood of a land cover in a particular area, thus the 3x3 transformed a pixel within a window equivalent to the ground dimension of 90 m x 90 m and the 7x7 transformed an area with a ground dimension of 210 m x 210 m.

A summary of the overall accuracy of the application of the filters is shown in Table 3-12. The application of the majority filter within the classes did not show much difference except that it tended to peak with the application of a 5x5 filter. When the filtered result was compared to the original classification, only the filtered refined and the classification with the added NDVI showed significantly improvement in the classification result over the original classification (Table 3-19).

Table 3-12: Summary of the overall accuracy for three types of majority filter applied to the classified images.

		Majority Filter (Types)			
Procedure		**No Filter**	**3 X 3**	**5 X 5**	**7 X 7**
Original Classification	**Overall Accuracy (%)**	**36.48**	**37.56**	**38.60**	**38.34**
	Kappa (%)	**26.83**	**27.85**	**28.69**	**28.15**
	Variance (kappa)	**7.7E-05**	**7.8E-05**	**7.9E-05**	**8.0E-05**
Refined Signatures	**Overall Accuracy (%)**	**39.75**	**41.73**	**42.42**	**40.83**
	Kappa (%)	**27.27**	**29.23**	**29.84**	**27.25**
	Variance (kappa)	**9.60E-05**	**9.88E-05**	**9.37E-05**	**1.02E-04**
NigeriaSat-1 + NDVI	**Overall Accuracy (%)**	**42.34**	**43.10**	**43.39**	**43.62**
	Kappa (%)	**29.23**	**29.74**	**29.86**	**29.73**
	Variance (kappa)	**2.97E-01**	**8.86E-05**	**8.99E-05**	**9.20E-05**

3.6.4 Merging of classes

The improvements applied to the classification of the 13 land cover classes did not significantly improve the overall accuracy of the classification. It was obvious that reaching the goal of improved accuracy would require the merger of some of the classes. This is common practice in image processing (Lillesand and Kiefer, 1999; Lawan, 1996). The merger of classes followed the classification scheme structure in which the 13 classes were grouped based on the results of the initial image classification. Thus all types of tree were grouped together, and similarly the individual classes within the new shrub-grass, bare ground and urban categories (Table 3-13). Furthermore an inspection of the errors within the groupings in the confusion matrices (Tables 3-7, 3-10, 3-11), showed that a large amount of the confusion arose within the grouping and although there was large confusion between trees and shrub-grass and between the shrub-grass and the bare ground, the conceptual construction of the grouping overrode this issue.

Table 3-13: New land cover categories following merger of the original 13 classes

New categories	Original Classes grouped
Tree	**High tree (mixed), Orchard, Short tree (mixed), Short tree (kwargo, *Bauhinia rufescence*)**
Shrub grass	**Shrub (mixed), Shrub (sabara, *Guiera senegalense*) Shrub grass, Grass**
Bare ground	**Bare ground, Bare ground clay, Bare ground gravel, Bare rock**
Urban	**Urban**

The merger was achieved in two ways: the first method built on the earlier classifications by merging the classes directly on the basis of the result of the classification and the confusion between the classes identified, similar to the approach of Lawan (1996). The results within the confusion matrices (Tables 3-7, 3-10 and 3-11) were used to achieve this. It was reasoned that the merger of the classes within the earlier classification would also integrate the improvement that had been achieved already in the process, although the errors remaining were also transferred. In order to check whether the product would be different had the signatures been merged prior to the classification, two other classification were conducted. The first method merged the spectral signatures and then applied the maximum likelihood classification and the second applied a parallelepiped algorithm followed by the maximum likelihood classification to classify the remaining unclassified pixels (Schowengert 2007; Alrababah and Alhamad, 2006). The reason for the second method was to see whether by relaxing the maximum likelihood condition the accuracy might improve. It was thought that the non homogeneity of the land cover might affect the structure of the image data therefore making it unsuitable for maximum likelihood classification. Using the second method a new land cover map was produced (Figure 3-9, and Full map at the end of the thesis).

The first procedure was accomplished by direct merger of the earlier classification trials (Tables 3-7, 3-10 and 3-11), thus producing Tables 3-14, 3-15 and 3-16, with respective accuracies of 56%, 60% and 61%. From the merger of the 13 classes which was the original classification, the producer accuracies after merger were greater than 60% except for shrub grass with less than 33%. The user accuracies were 50% or better. There was still a high degree of misclassification of bare ground and shrub grass, and shrub grass and tree. In the merged refined classification (Table 3-15) all of the producer and user accuracies were over 50%. The user accuracy of the urban was 96% meaning that most of the pixels classified as urban were indeed urban.

The result of the direct merger of spectral signatures and classifying by maximum likelihood is shown in Table 3-17 and the results of the implementation of the parallelepiped and maximum likelihood classifiers can be seen in Table 3-18. The results were significantly different from the earlier trials and the two were comparable to the accuracies achieved by Lawan (1996).

Table 3-14: Confusion matrix for merged classes from the original classification of the NigeriaSat-1 image

		Reference					
		Tree	Shrub-grass	Bare ground	Urban	Row Total	User Accuracy (%)
Classified	Tree	523	405	127	0	1055	49.57
	Shrub grass	17	424	401	13	855	49.59
	Bare ground	97	446	910	3	1456	62.50
	Urban	1	5	14	62	82	75.61
	Column Total	638	1280	1452	78	3448	
	Producer Accuracy (%)	81.97	33.13	62.67	79.49		
Overall Accuracy (%)		55.66					
Kappa (%)		34.11					
Variance (kappa)		0.0002					

Table 3-15: Confusion matrix for merged classes from the refined spectral signatures

		Reference					
		Tree	Shrub grass	Bare ground	Urban	Row Total	User Accuracy (%)
Classified	Tree	397	163	41	1	602	65.95
	Shrub grass	58	740	580	10	1388	53.31
	Bare ground	124	376	830	13	1343	61.80
	Urban	2	1	1	54	58	93.10
	Column Total	581	1280	1452	78	3391	
	Producer Accuracy (%)	68.33	57.81	57.16	69.23		
Overall Accuracy (%)		59.60					
Kappa (%)		37.37					
Variance (kappa)		0.0002					

Table 3-16: Confusion matrix for merged classes from the NigeriaSat-1 image plus NDVI'

		Reference					
		Tree	Shrub	Bare ground	Urban	Row Total	User Accuracy (%)
Classified	Tree	431	144	49	0	624	69.07
	Shrub	97	554	342	4	997	55.57
	Bare ground	110	582	1061	14	1767	60.05
	Urban	0	0	0	60	60	100.00
	Column Total	638	1280	1452	78	3448	
	Producer Accuracy (%)	67.55	43.28	73.07	76.92		
Overall Accuracy (%)		61.08					
Kappa (%)		39.47					
Variance (kappa)		0.0002					

Table 3-17: The classification of NigeriaSat-1 using merged spectral signatures and the maximum likelihood classifier

		Reference					
		Tree	Shrub-grass	Bare ground	Urban	Row Total	User Accuracy (%)
Classified	Tree	509	215	57	0	781	65.17
	Shrub grass	81	734	531	9	1355	54.17
	Bare ground	15	274	812	7	1108	73.29
	Urban	33	57	52	62	204	30.39
	Column Total	638	1280	1452	78	3448	
	Producer Accuracy (%)	79.78	57.34	55.92	79.49		
Overall Accuracy (%)		61.40					
Kappa (%)		42.86					
Variance (kappa)		0.0002					

Table 3-18: The classification of the NigeriaSat-1 image using the parallelepiped and maximum likelihood classifiers

		Reference					
		Tree	**Shrub-grass**	**Bare ground**	**Urban**	**Row Total**	**User Accuracy (%)**
Classified	**Tree**	**515**	**213**	**56**	**0**	**784**	**65.69**
	Shrub grass	**88**	**640**	**405**	**4**	**1137**	**56.29**
	Bare ground	**15**	**385**	**952**	**12**	**1364**	**69.79**
	Urban	**20**	**42**	**39**	**62**	**163**	**38.04**
	Column Total	**638**	**1280**	**1452**	**78**	**3448**	
	Producer Accuracy (%)	**80.72**	**50.00**	**65.56**	**79.49**		
Overall Accuracy (%)		**62.91**					
Kappa (%)		**44.46**					
Variance (kappa)		**0.0002**					

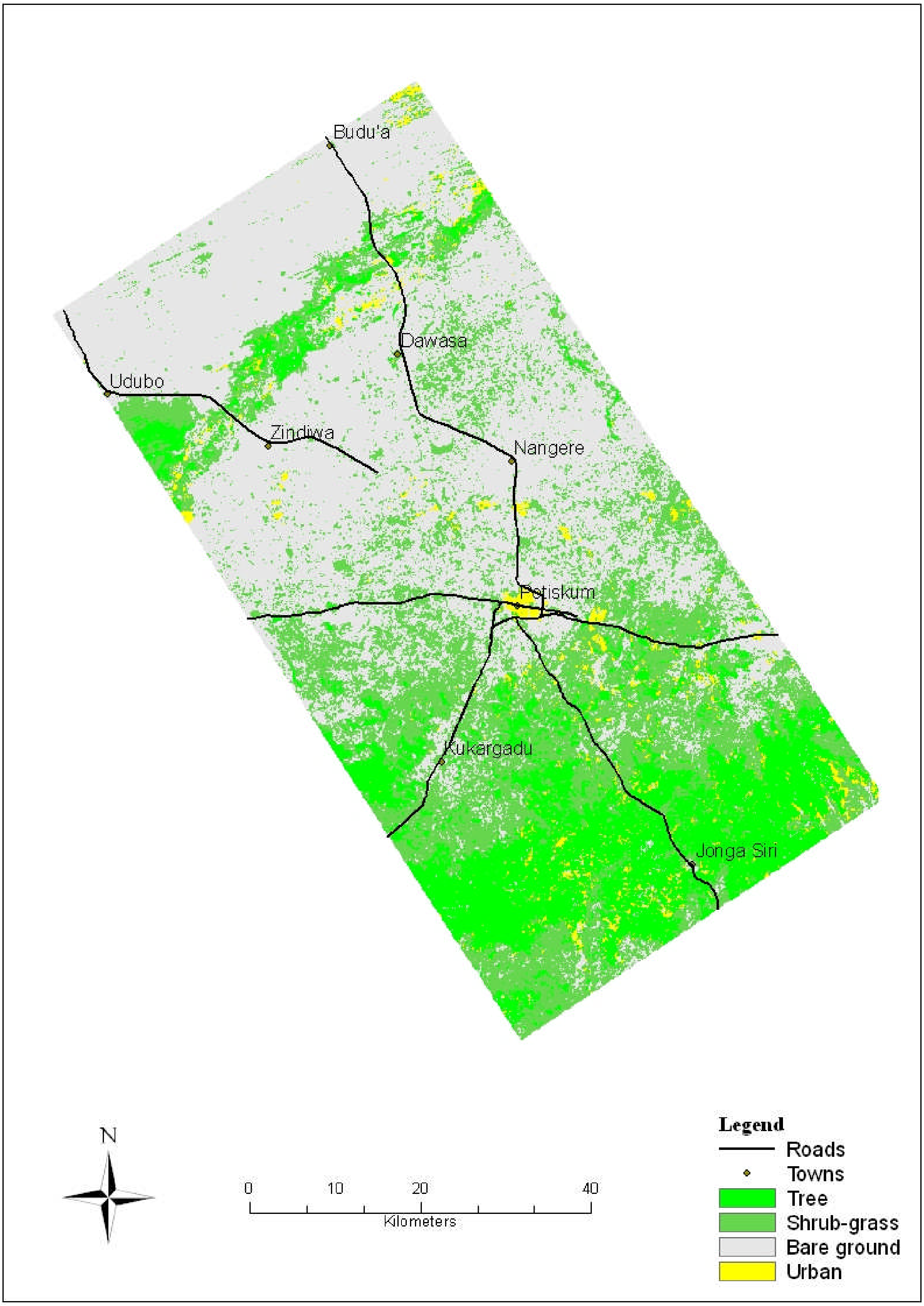


Figure 3-9: The original 13 class classification of the NigeriaSat-1 image merged into four categories

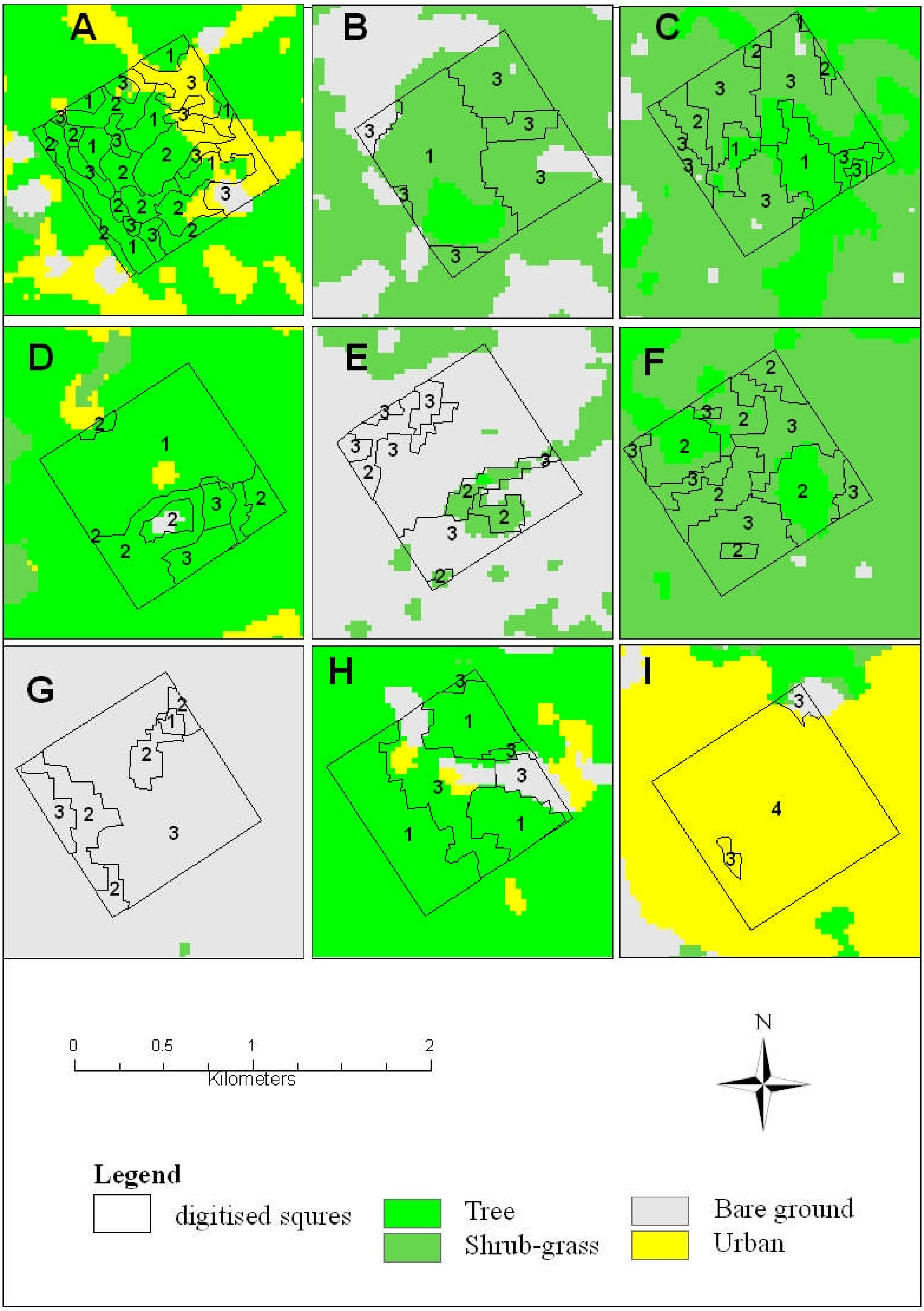


Figure 3-10: The merged land cover category classification of the NigeriaSat-1 image within selected field survey squares. Merged field survey data is shown as outline polygons, with the numbers 1 = Tree; 2 = Shrub grass, 3 = Bare ground and 4 = Urban

3.7 Comparison of the Confusion Matrices

A comparison was undertaken to test whether the kappa resulting from two confusion matrices (K_1 and K_2) were different. This test used the standardized normal distribution (Equation 3-7), (Congalton and Green, 1999) hence the null hypothesis was set as: Ho: K_1=K_2 and the alternative hypothesis $K_1 \neq K_2$.

The result of the kappa comparison is shown in Table 3-19 and the alternative chi square approach in Table 3-20. It is possible that the two results are different because of the covariance in Equation 3-8, however, only the merged original classification among the merged classifications showed that method 1 stood out to be the inferior approach. This indicated that any of the improvement procedures was better than method 1 and although not completely true, there was still the indication that by merging and manipulating the signature prior to the classification a better classification resulted.

When comparing the classification of individual merged land cover types (Tables 3-21, 3-22 and Figures 3-9 and 3-10), the urban land cover had the highest accuracy amongst the methods except when method 4 was used as indicated by the large standard deviation in the urban user accuracy (Table 3-20 and Figure 3-12). This could mean that all methods favoured the classification of the urban class except method 4.

Table 3-19: Comparison of the confusion matrices using kappa statistics.

		1	2	3	4	5	6	7	8	9	10	11
Table 3-7	1. NigeriaSat-1		NS	NS	NS	S	S	S	S	S	S	S
Table 3-8	2. Refined	0.30		NS	NS	NS	NS	S	S	S	S	S
Table 3-9	3. NigeriaSat-1+NDVI	1.87	1.47		NS	NS	NS	S	S	S	S	S
Table 3-10	4. NigeriaSat-1(Majority Filter)	1.49	1.11	0.42		NS	NS	S	S	S	S	S
Table 3-10	5. Refined(majority Filter)	2.30	1.90	0.45	0.87		NS	S	S	S	S	S
Table 3-10	6. NigeriaSat-1+NDVI(Majority)	2.35	1.93	0.47	0.90	0.01		S	S	S	S	S
Table 3-11	7. NigeriaSat-1 (Merged)	4.37	4.00	2.88	3.24	2.49	2.50		NS	S	S	S
Table 3-12	8. Refined (Merged)	6.58	6.13	5.04	5.44	4.63	4.65	1.84		NS	S	S
Table 3-13	9. NigeriaSat-1+NDVI (merged)	7.59	7.11	6.03	6.45	5.62	5.64	2.68	0.84		S	S
Table 3-14	10. Direct classification of four categories (maximum likelihood)	9.63	9.08	8.03	8.48	7.60	7.64	4.38	2.54	2.54		NS
Table 3-15	11. Direct classification of four categories (parallelepiped + maximum likelihood)	10.59	10.01	8.97	9.44	8.53	8.57	5.18	3.34	2.50	0.80	

Table 3-20: Chi-square pair wise comparison of confusion matrices.

		1	2	3	4	5
Table 3-11	Method 1. NigeriaSat-1 (merged)		S	S	S	S
Table 3-12	Method 2. Refined (merged)	10.89		NS	NS	S
Table 3-13	Method 3. NigeriaSat-1+NDVI (merged)	20.86	1.56		NS	S
Table 3-14	Method 4. Direct classification of four categories (maximum likelihood)	23.42	2.32	0.7		NS
Table 3-15	Method 5. Direct classification of four categories (parallelepiped + maximum likelihood)	37.55	7.88	2.41	1.67	

Table 3-21 Comparison of the user and producer accuracies of merged land covers categories by classification method

	Original thirteen classes merged		Refined thirteen classes merged		Original +NDVI classes merged		Merged signature maximum likelihood		Merged signature parallelepiped + maximum likelihood	
	Producer Accuracy %	User Accuracy %	Producer Accuracy (%)	User Accuracy %	Producer Accuracy %	User Accuracy %	Producer Accuracy %	User Accuracy %	Producer Accuracy %	User Accuracy %
Tree	81.97	49.57	68.33	65.95	67.55	69.07	79.78	65.17	67.55	80.72
Shrub	33.13	49.59	57.81	53.31	43.28	55.57	57.34	54.17	43.28	50
Bare ground	62.67	62.5	57.16	61.8	73.07	60.05	55.92	73.29	73.07	65.56
Urban	79.49	75.61	69.23	93.1	76.92	100	79.49	30.39	76.92	79.49

Table: 3-22 Average producer and user accuracies and their standard deviations

	Mean producer accuracy	Standard deviation	Mean user accuracy	Standard deviation
Tree	73.04	7.20	66.07	11.14
Shrub	46.97	10.53	52.53	2.63
Bare ground	64.38	8.33	64.64	5.23
Urban	76.41	4.21	75.72	27.21

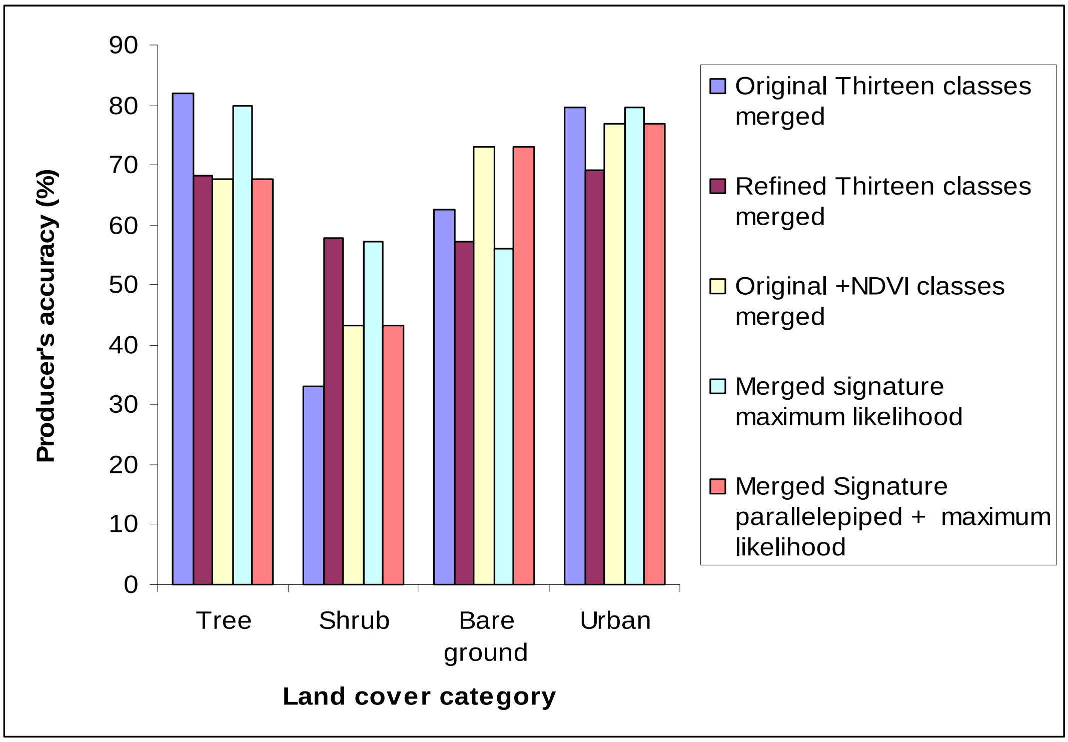


Figure 3-11: Comparison of the producer accuracies for the five classification methods used

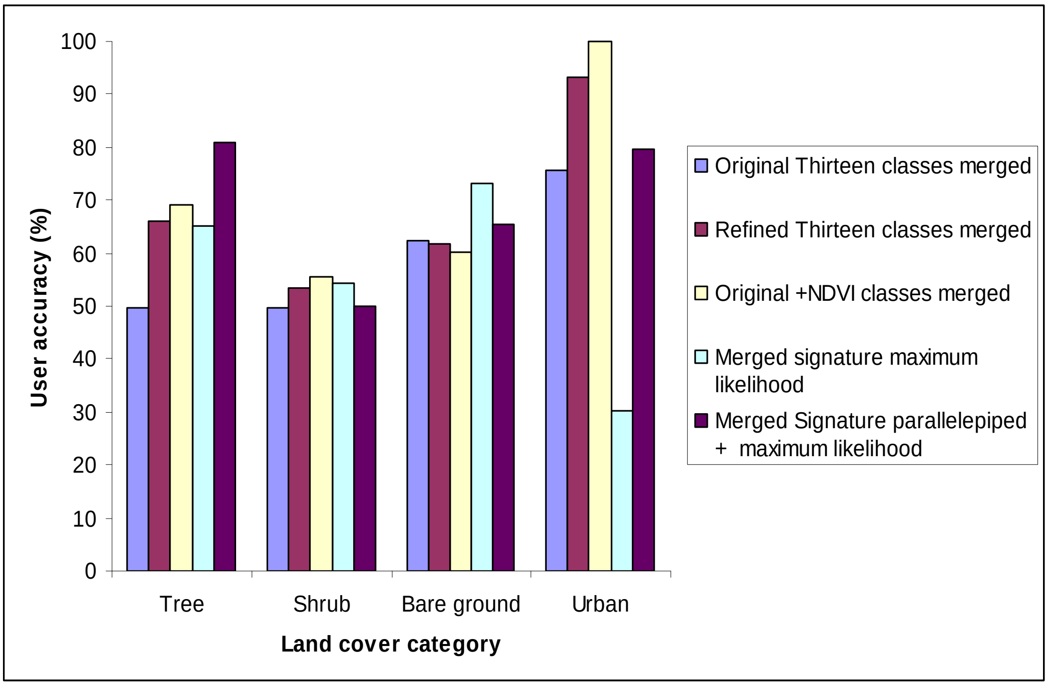


Figure 3-12: Comparison of the user accuracies for the five classification methods used

3.8 Summary of the Classification of NigeriaSat-1 Imagery

The attempt to classify the NigeriaSat-1 image into 13 classes is a representation of the potential needs that could arise from general users of land cover mapping in the north east of Nigeria. This will include the desire to manage the scarce and scattered woodland, the shrub grass associated with rangeland, the cultivated land which is bare ground during the dry season, the bare barren lands which could be degraded land and the development of urban areas. The classification of NigeriaSat-1 with the 13 land cover classes tested the capability of undertaking such a classification during the dry season when the vegetation in the area is under heat stress, grasses almost dry and dead. Overall, the basic classification of NigeriaSat-1 with 13 classes did not produce the desired accuracy.

The pre classification analysis both graphically and quantitatively showed few exclusive separations in the line plot and no exclusiveness in the histogram plot. It also showed multimodality in many of the land cover types. This helped to explain the difficulty achieving good results in the 13 class classification. The dual action of subsetting those land covers exhibiting multimodality and applying separability analysis which was followed either by elimination or merger; partly showed the mixture of pixels that make up the land cover. Thus the inseparability between the classes was not only due to the lack of spectral distinctiveness between the land covers but also because the land covers as defined were heterogeneous in nature.

Only very few of the land covers were classified relatively well, for example, short tree kwargo, *Bauhinia rufescence* and urban classes. The group of land covers belonging to the shrub grass were the most poorly classified. The effect of their poor classification was such that the overall accuracy changed from 36% to 70% when the elements of the group were removed from the accuracy assessment. This effect was the subject for further investigation.

Attempts were made to improve the classification with the 13 classes by refining the spectral signatures. The refinements addressed the heterogeneous nature of the landscape and the definition of land covers that made up the spectral signatures. This was directed at the possible multimodal probability density function and separability distance. The refinement also tried to enhance the image by adding an NDVI layer. These approaches did not produce significantly different results compared with the original classification until the majority filter was applied. The overall accuracy remained about 40%.

The application of the majority filter did not seem to alter the classification result significantly for a particular method. However, in the little variation that was apparent, the highest overall accuracy compared to the original and the refined spectral signature methods was with the application of the 5x5 majority filter. It is possible that the nature of the landscape, that is, scattered vegetation, makes the choice of a higher dimension filter unsuitable. This needs to be further investigated, that is, the choice of majority filter in relation to the corresponding shape and size of the potential mapping units.

One of the logical ways of dealing with low classification accuracy was to merge the 13 classes into 4 meaningful categories. The merger was also important to provide categories that could be interpreted and classified on the historical images where no reference data existed (Chapter 4). The merger was undertaken in two ways: the first was the merger of the result already obtained and the second approach was the merger of the original spectral signatures and then classified by two methods.

Although the overall accuracies of the different classifications were generally low, they were within the general accuracy that could be produced by this type of survey (Foody 2006; Sannier 2000; Abdalla 1994; Lawan 1996). One would tend to agree with Foody (2006) when he states the remote sensing community is being too harsh in regard to its method of accuracy assessment.

Chapter 4 Classification of Land Cover for 1986 and 2000

4.1 Introduction

This chapter presents the classification of the Landsat TM of 1986 and Landsat ETM+ of 2000. This was done to create historical land cover data in order to facilitate change analysis. The two Landsat images are the only available data similar to the NigeriaSat-1 imagery that could be subjected to similar processes and with similar outcomes and level of accuracy. In order to conduct a supervised classification of the Landsat data a reference dataset was required, which was also not available in this study. Thus the first task was to visually interpret the Landsat data in order to produce a reference dataset, and use this as a basis for classification and accuracy assessment. The interpretation was done with the aid of interpretation keys. The keys served as training for the manual interpretation and a means of maintaining consistency in the interpretation (Lillesand and Kiefer 1999).

This was undertaken by interpreting a sample of the land cover categories similar to the 2006 field reference data. The Landsat images were then classified first using the equivalent bands of the NigeriaSat-1 image and then using the middle infrared bands. The use of the image in two ways was an attempt to determine whether the addition of the middle infra red would affect the classification result.

The difference between the NigeriaSat-1 image and Landsat TM and the ETM+ images was the presence of the thermal and two middle infrared (MIR) bands, band 5 (1.55 - 1.75 µm) and band 7 (2.08 – 2.35 µm). Band 5 is said to be sensitive to water moisture (Jensen, 2000; Wilson and Sader, 2002) and Band 7 (2.08 – 2.35 µm) effective for discrimination of geological formations (Jensen, 2000).

4.2 Creating a reference map for Landsat TM and ETM+ imagery

Creating reference data in the case of this research was essentially an interpretation task, since the process involved the use of certain criteria to identify the land cover on the image. The method of visual image interpretation is sometimes thought to produce better classifications, however it is laborious and its accuracy is subject to the experience of the interpreter (Bird et al., 2000; Lillesand and Kiefer, 1999). The use of image interpretation in this work was limited to areas where sample squares had already been taken in the field to maintain consistency with the approach taken with the NigeriaSat-1 classification.

As in the case of the NigeriaSat-1 imagery the spatial resolution (30 m) of the Landsat ETM+ and TM images did not automatically reveal land cover categories and it therefore limited the application of interpretation factors such as shadow, pattern, size and texture (Lillesand and Kiefer, 2000). However, the field survey data and the NigeriaSat-1 imagery provided the first means of defining the image characteristics of the land cover categories. This was because of the similarities of the images; it could be assumed that the characteristics of the land categories in the two image types would be the same.

The strategy was to first develop keys for interpreting each land cover category and then use the keys to interpret the 50 sample squares. To develop a key for a particular land cover, the position of the land cover in 2005 was used as the basis for identifying the location of the land cover on the earlier dates of imagery. This approach was adopted working on the assumption that categorical land cover changes were marginal in many cases (Pontius et al. 2004), that is, there were high chances of land cover categories persisting that did not wholly change. This will be particularly true if it is assumed that areas of land cover retain their overall shapes and patterns in relation with their neighbours. This assumption was checked after identifying a potential feature to be used as a key for the interpretation by comparing the relative tonal difference within the neighbourhood, and where available, knowledge of the area was used to reinforce the interpretation.

4.2.1 Urban

The urban land cover was not obvious in the NigeriaSat-1 image. Without a visible road network and field knowledge of the area it was difficult to identify, and sometimes it conflicted tonally with other features such as the bare rocky surface (Figure 4-1). When magnified (Figure 4-5), it was still hard to define a particular characteristic of the feature. At a spatial resolution of about 30m, no pattern, shapes or sizes of urban structures within the land cover was discernible. However, identifying the urban land cover was eased by using the field survey experience and knowledge of the area. The urban category has some textual differences compared with the tree and bare rocky surface (Figure 4-1) and on the NDVI image (Figure 4-2) it has a darker tone compared to the tree category. When magnified, the textural variation was still higher (Figure 4-5) compared to the other classes (compare Figures 4-1 and 4-5 to Figures 4-6, 4-9, 4-10, and 4-11). However, many smaller towns could not be identified without the knowledge of the area. In the panchromatic band from the ETM+ image, some patterns that could be identified and inferred such as town streets could be seen (Figure 4-4). The pattern was only visible in the eastern part of the town and was the only location with such a pattern in the study area. The false colour composite of the Landsat ETM+ image also did not clearly distinguish the urban area without some prior knowledge. As far as this work was concerned the main sample square with urban land cover fell within the town identified.

4.2.2 Tree

The interpretation of the tree category was started by looking at its characteristics in the NigeriaSat-1 image. The tree category appeared for example in sample squares 11, 31, and 41 shown in Figure 4-6 as a, b, c. Even though the images were magnified (Figure 4-9), there were no discernable patterns, shapes or size that could be seen within the tree category except for relative tonal differences with other categories. The tree had a dark tone in the composite image (Figure 4-6a. b and c). It was checked to see whether a particular waveband would distinguish the tree, but this was not successful as no visual difference could be discerned between the images (Figure 4-7). However, the NDVI image did show the tree as lighter or whiter (Figure 4-5 d, e and f), with the same characteristics when the image was magnified to the scale of 1:10,000 (Figure 4-7 a, b).
The locations of trees were selected from the 2006 field survey, and then their corresponding locations were checked to see whether the shapes and patterns in the area were evident in 2000 and/or in 1986. If they were not then they were eliminated from the choice of being used as a key. If they remained the same, they were then checked for tonal characteristics to see whether the tree identified had the equivalent tone as tree in the NigeriaSat-1 and the NDVI images (Figures 4-6, 4-8, and 4-9).

4.2.3 Shrub grass

The shrub grass category as with the tree category could not be distinguished by characteristics such as size, shape and pattern. It had a lighter tone than the tree category in the RGB image composite (Figure 4-5 a, b and c). The shrub grass category also had a slightly darker tone than bare round. It was relatively darker than tree in the NDVI image. When the image was zoomed to a scale of 1:10,000, the tonal characteristics remained the same (Figure 4-8 a and b). This category was then interpreted in similar ways to the tree category, using the same sample squares that had tree and shrub grass lying side by side.

4.2.4 Bare ground

Bare ground was a mixture of sandy soil, clay and rocky surfaces which were not covered by vegetation or built up areas. The tone was generally light with little variation because of the soil types. However, the NDVI response was dark, and relative to the other land cover categories, it showed the darkest response (Figure 4-6 a, b, c, d, e and f). When zoomed to the scale 1:10,000 (Figure 4-11 a and b) the same characteristics were expressed by the image.

4.2.5 General comments on the land cover characteristics and their use in the historic interpretation

As large as Potiskum town (about 12 km^2) was, the image did not reveal a clearly distinct spectral response that could be classified as urban in the NigeriaSat-1 imagery. Therefore, without other information the NigeriaSat-1 imagery was not able to provide sufficient interpretation material for the urban land cover, this also applied to the Landsat TM and ETM+ (without the panchromatic). If the interpretation was limited to tree, shrub grass and bare ground, then it was easier to discriminate between the tree and the bare ground using the RGB image composite and the NDVI; in the RGB the tree was dark while bare ground was light and in the NDVI they had the reverse appearance. The shrub grass category tended to have an appearance midway between the tree and the bare ground, and sometimes was difficult to differentiate from tree and bare ground. The separate wavebands did not appear to give any advantage over the composite of the three bands (Figures 4-6, 4-7, 4-8). In some cases it took more than the interpretative elements of the NigeriaSat-1 to interpret the historical images in the study area.

In order to bring out the characteristics of the urban category the following questions were asked: can urban be visually identified and can it be properly delineated, and what are the factors that distinguish it from others. Answering the question as to whether the extent of the urban category could be delineated, it was easier to demarcate the boundary of the urban area on the Landsat ETM+ panchromatic image (Figure 4-9). But the question of whether the experiences of interpreting the urban land cover of Potiskum could be easily transferred will depend on the size of the town, whether there are roads, whether there are identifiable features and whether ancillary data is available.

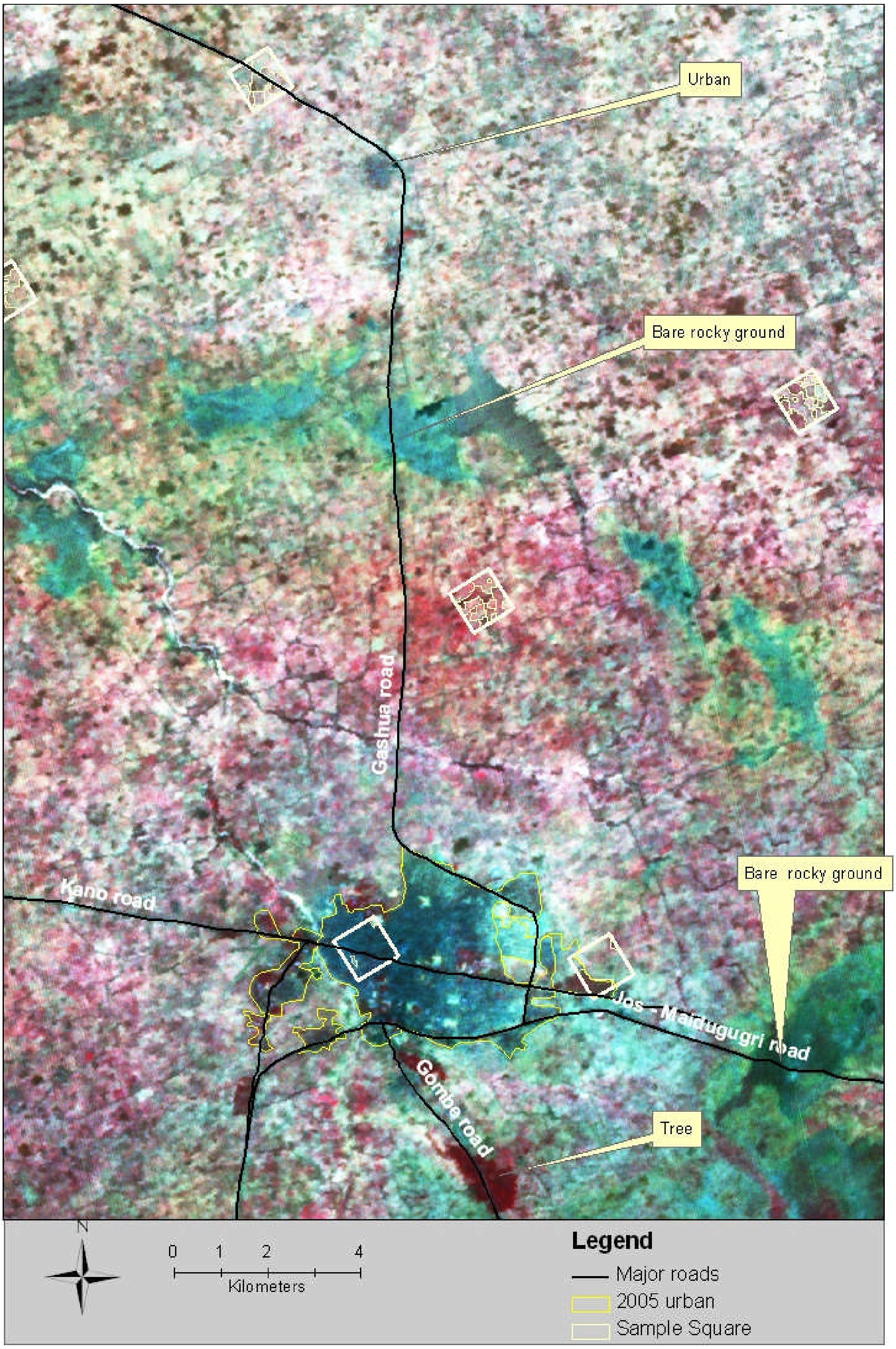


Figure 4-1: The urban land cover compared to the bare ground in the NigeriaSat-1 image

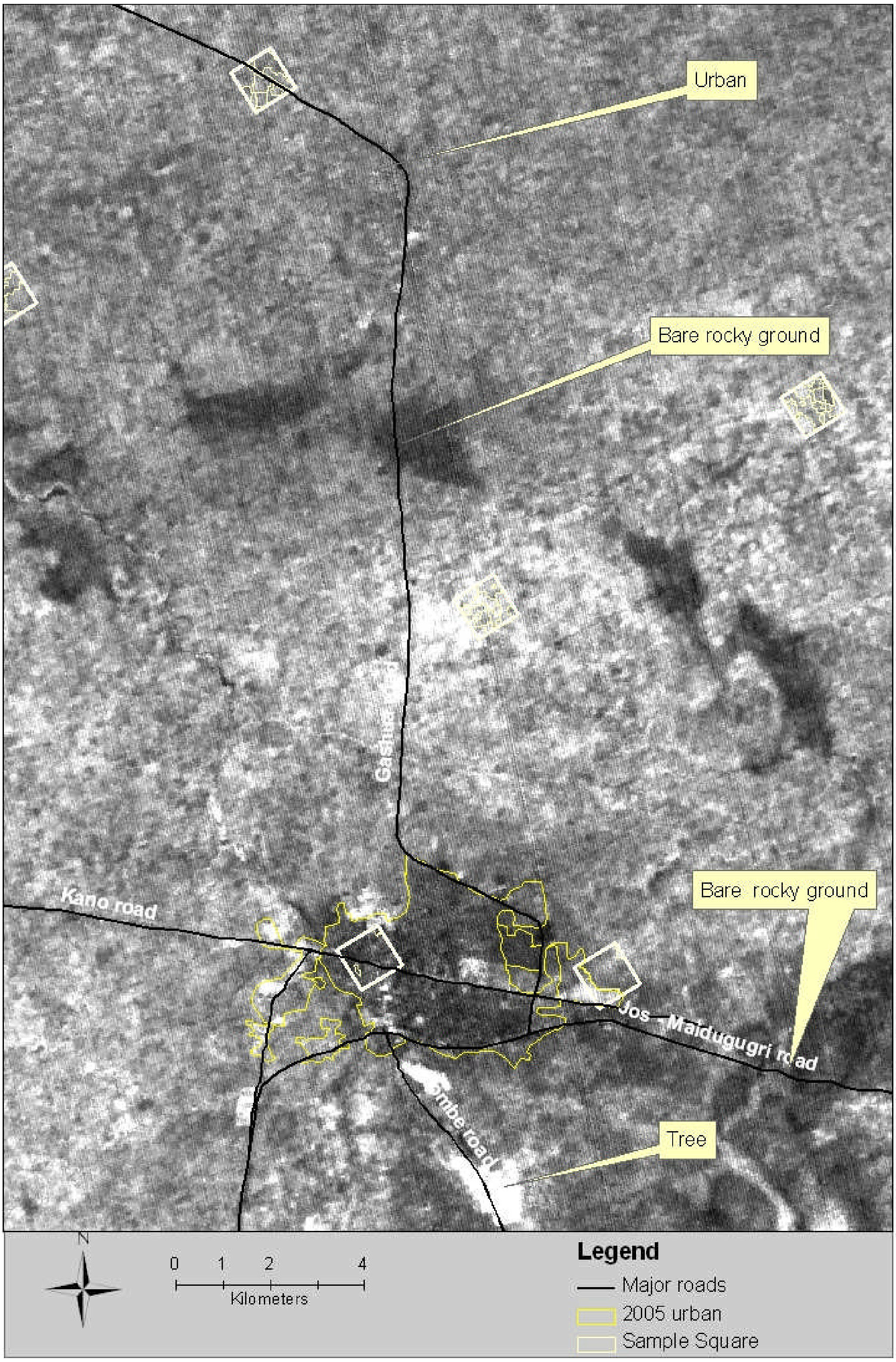


Figure 4-2: The urban land cover compared to the bare ground in the NDVI of the NigeriaSat-1

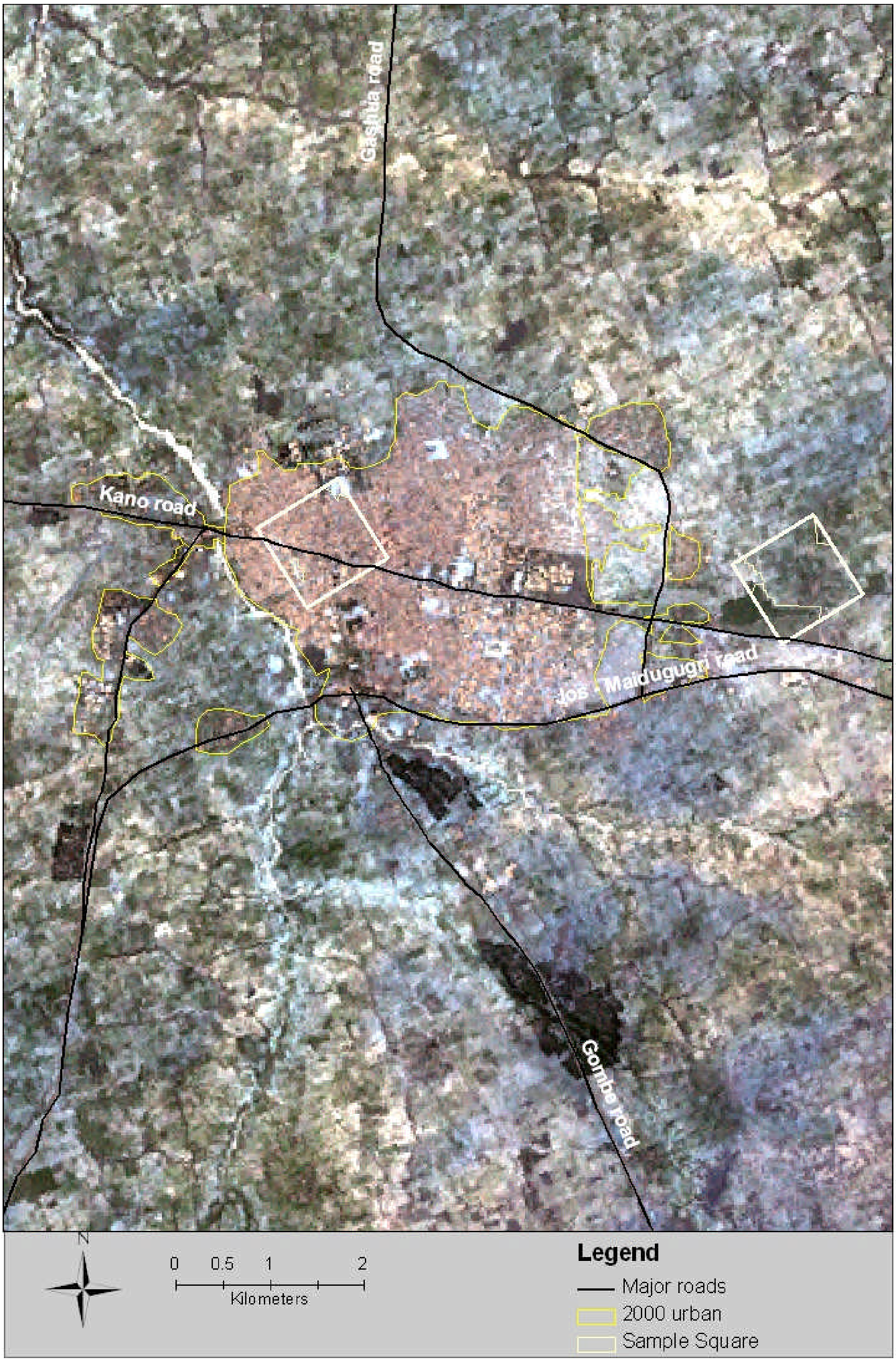


Figure 4-3: The urban land cover in the Landsat ETM+ image composite of wavebands 2, 3, 4 for the year 2000

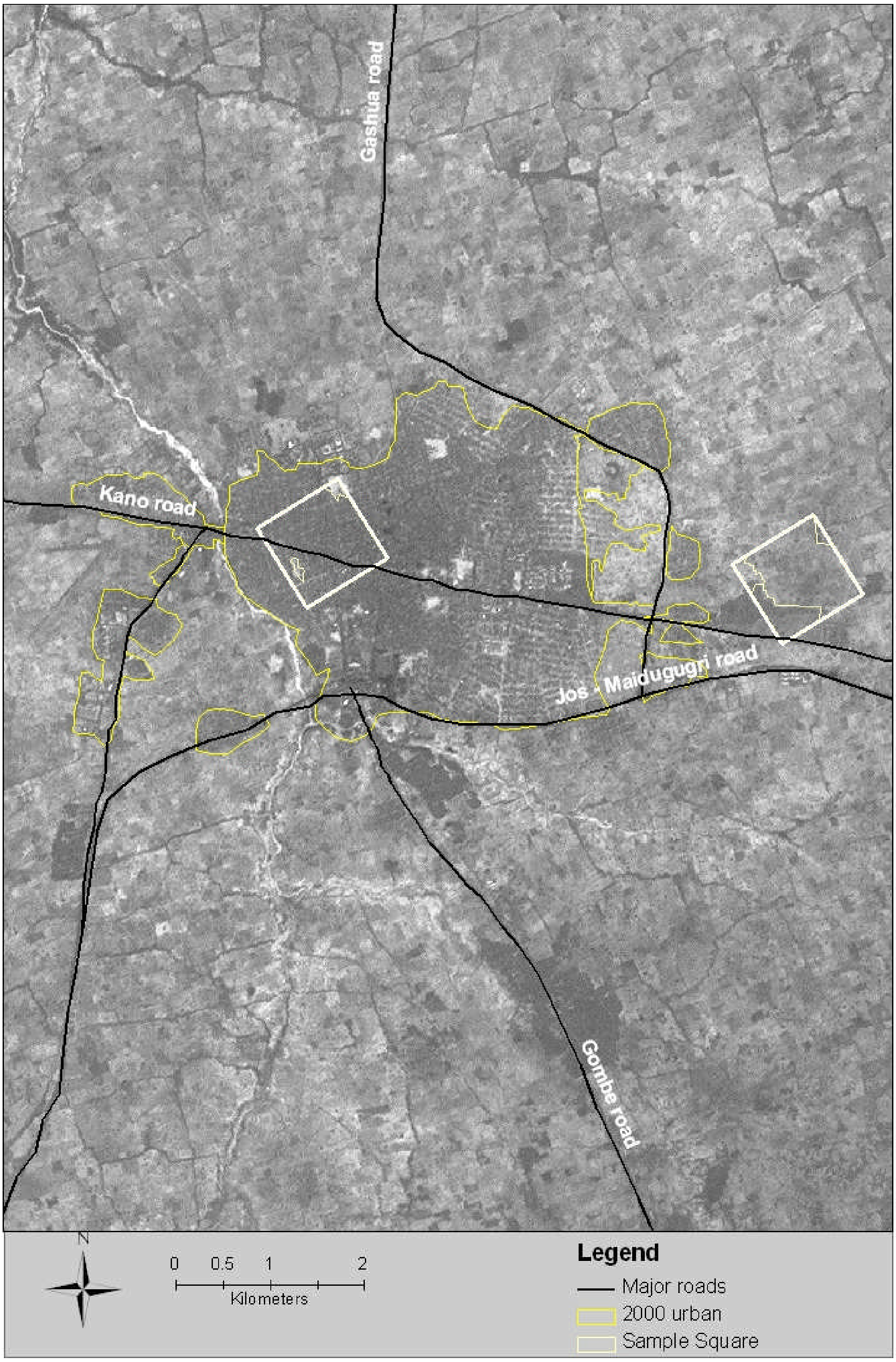


Figure 4-4: The urban land cover in the Landsat ETM+ panchromatic waveband for the year 2000

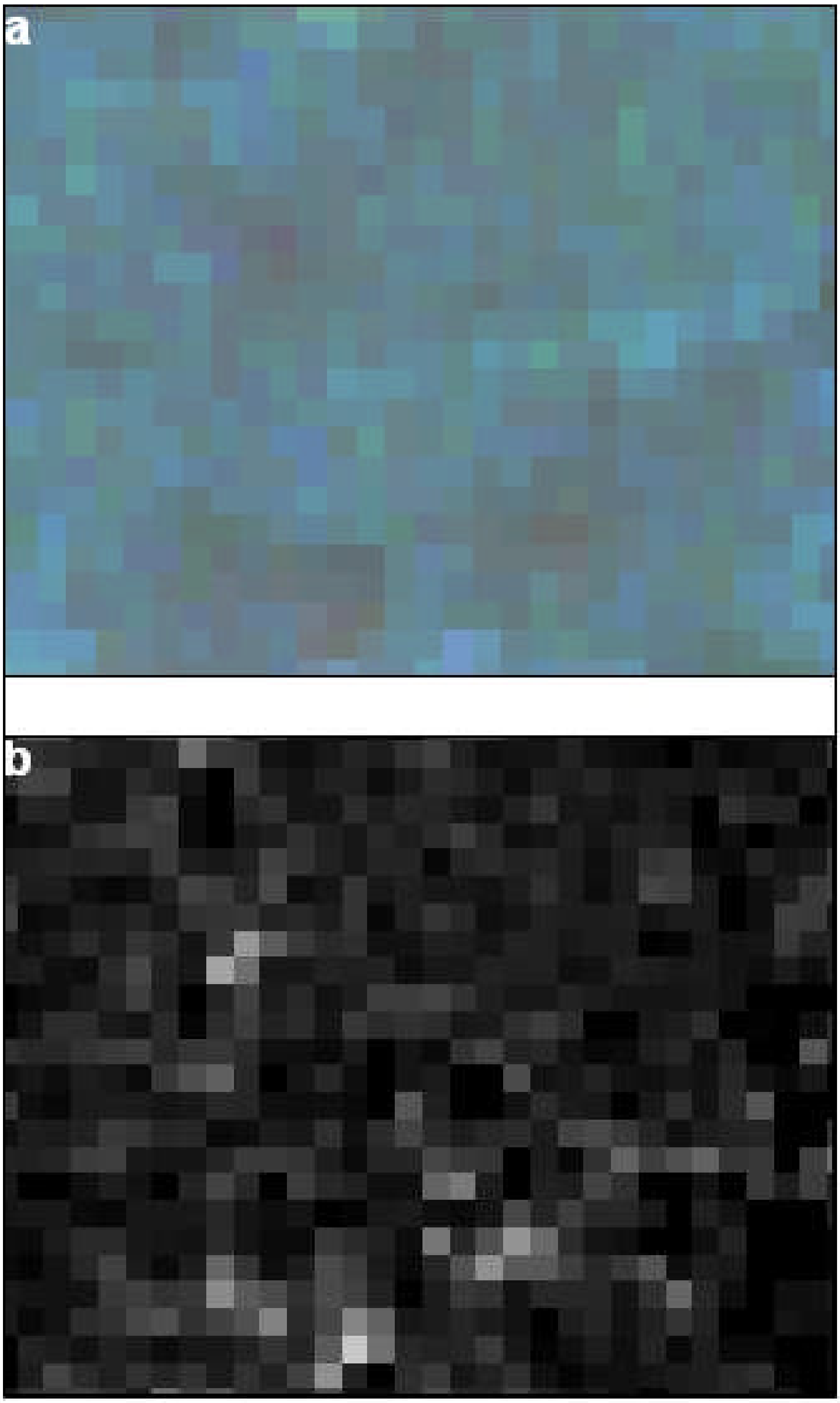


Figure 4-5: The magnified urban land cover found in a). NigeriaSat-1 and b). NDVI of NigeriaSat-1

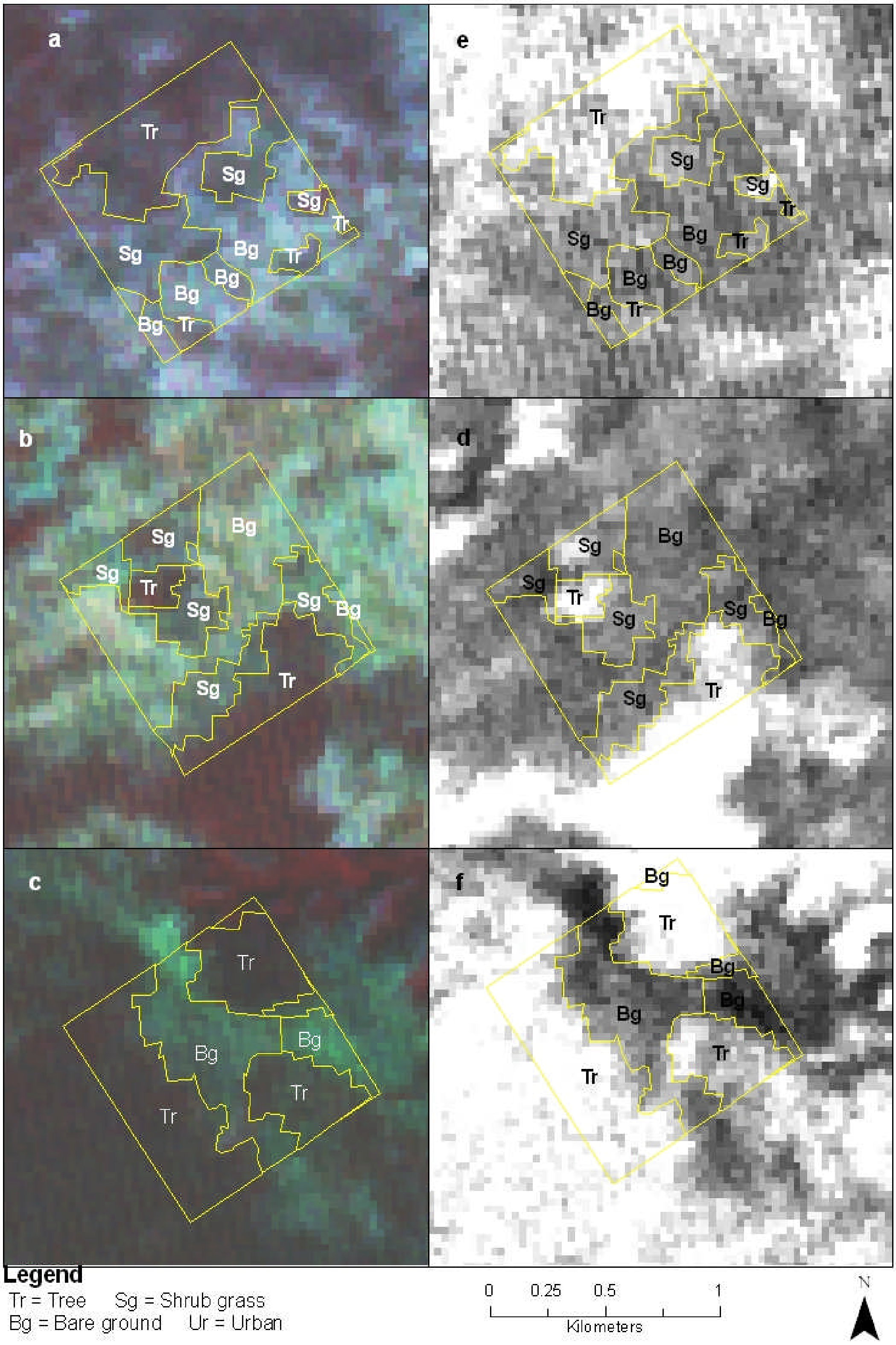


Figure 4-6: Example of the land cover categories from the NigeriaSat-1 and NDVI image derived from NigeriaSat-1. Images a, b, and c are NigeriaSat-1 false colour composites illustrating samples from the Fadama area, the Potiskum plain and the southern part of the study area, respectively, and images d, e and f are their respective NDVI images.

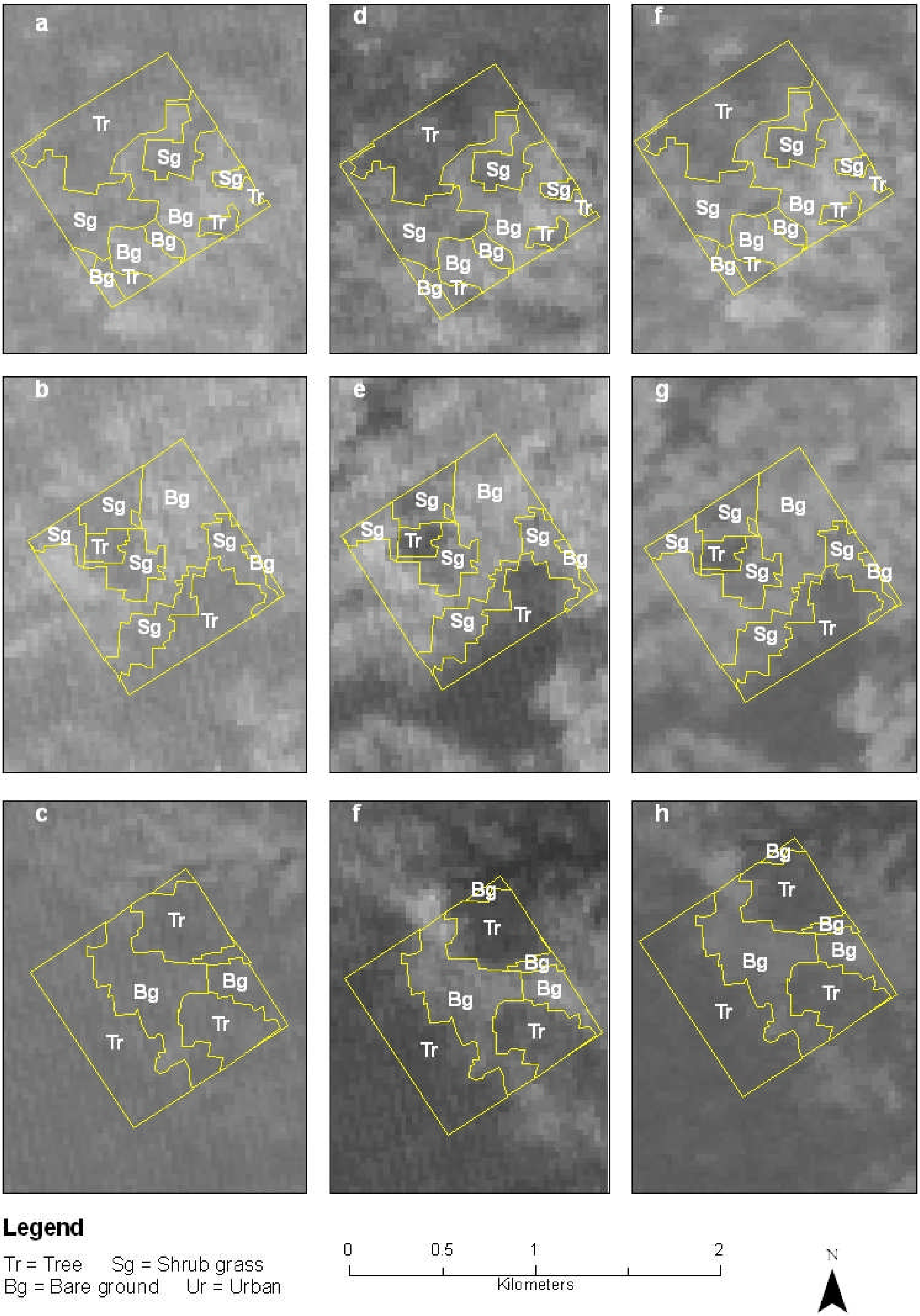


Figure 4-7: Examples of the land cover categories from the three separate wavebands of the NigeriaSat-1 image for sample squares no 11, and 41 in descending order. Images a, b, and c are wave band 1 (infrared); images d, e and f are waveband 2 (red) and images g, h and i are waveband 3 (green). They illustrate sample land cover categories from the Fadama area, the Potiskum plain and the southern part of the study area.

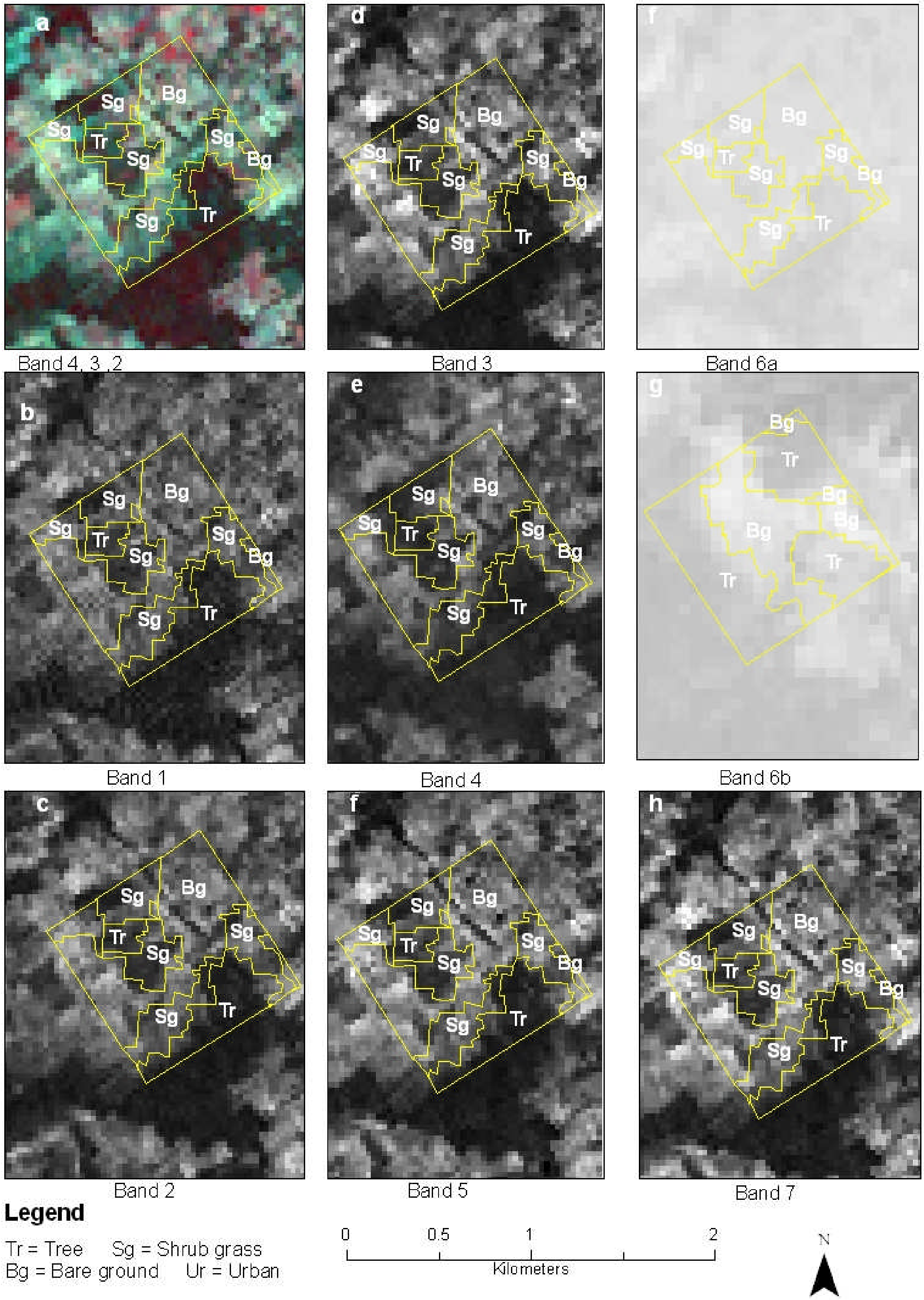


Figure 4-8: The appearance of tree, shrub grass and bare ground in composite and single wavebands of the Landsat ETM+ image

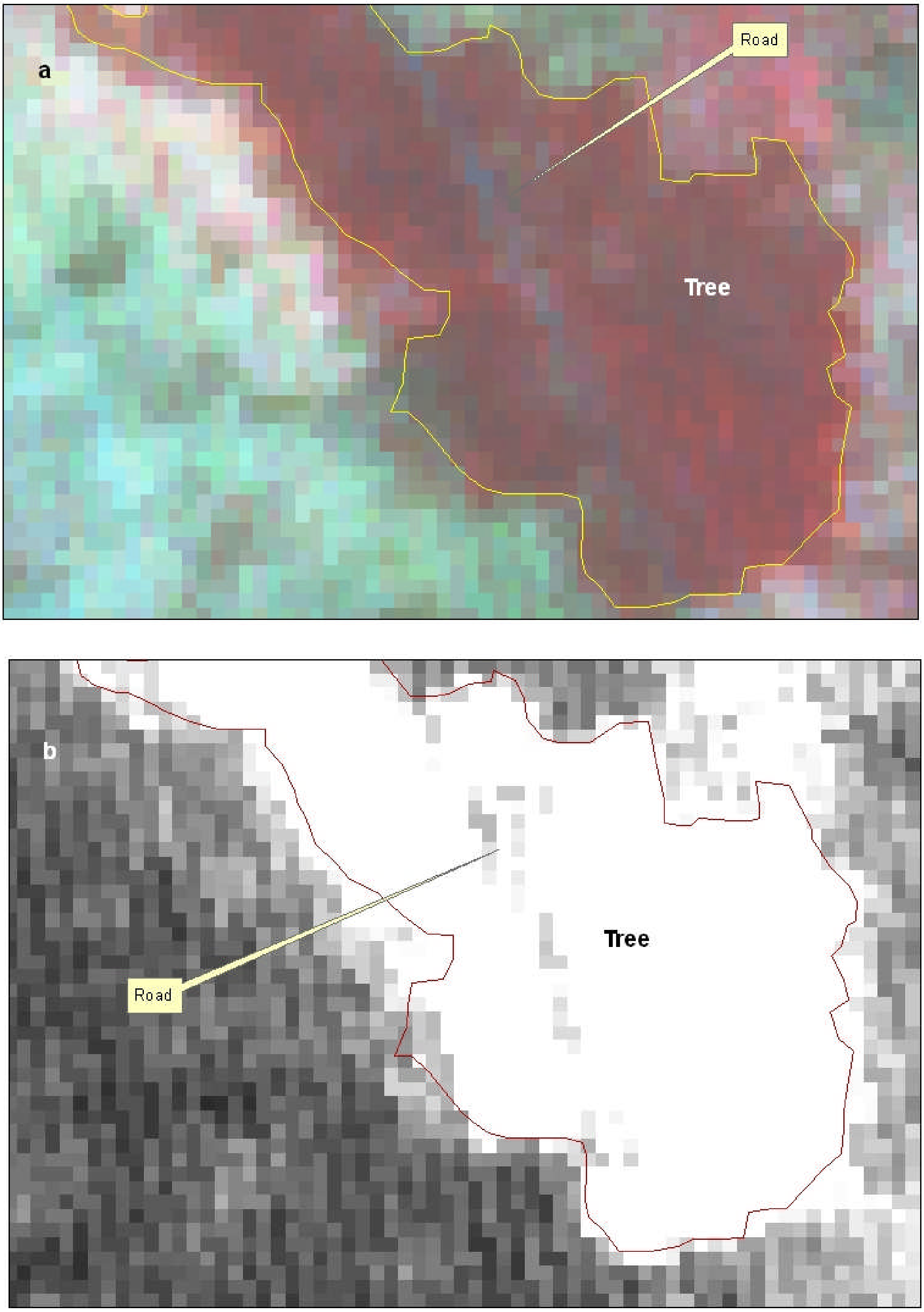


Figure 4-9: Illustration of a magnified image of the tree category in the Landsat ETM+ image: a). wavebands 2, 3, 4 false colour composite, b). NDVI image

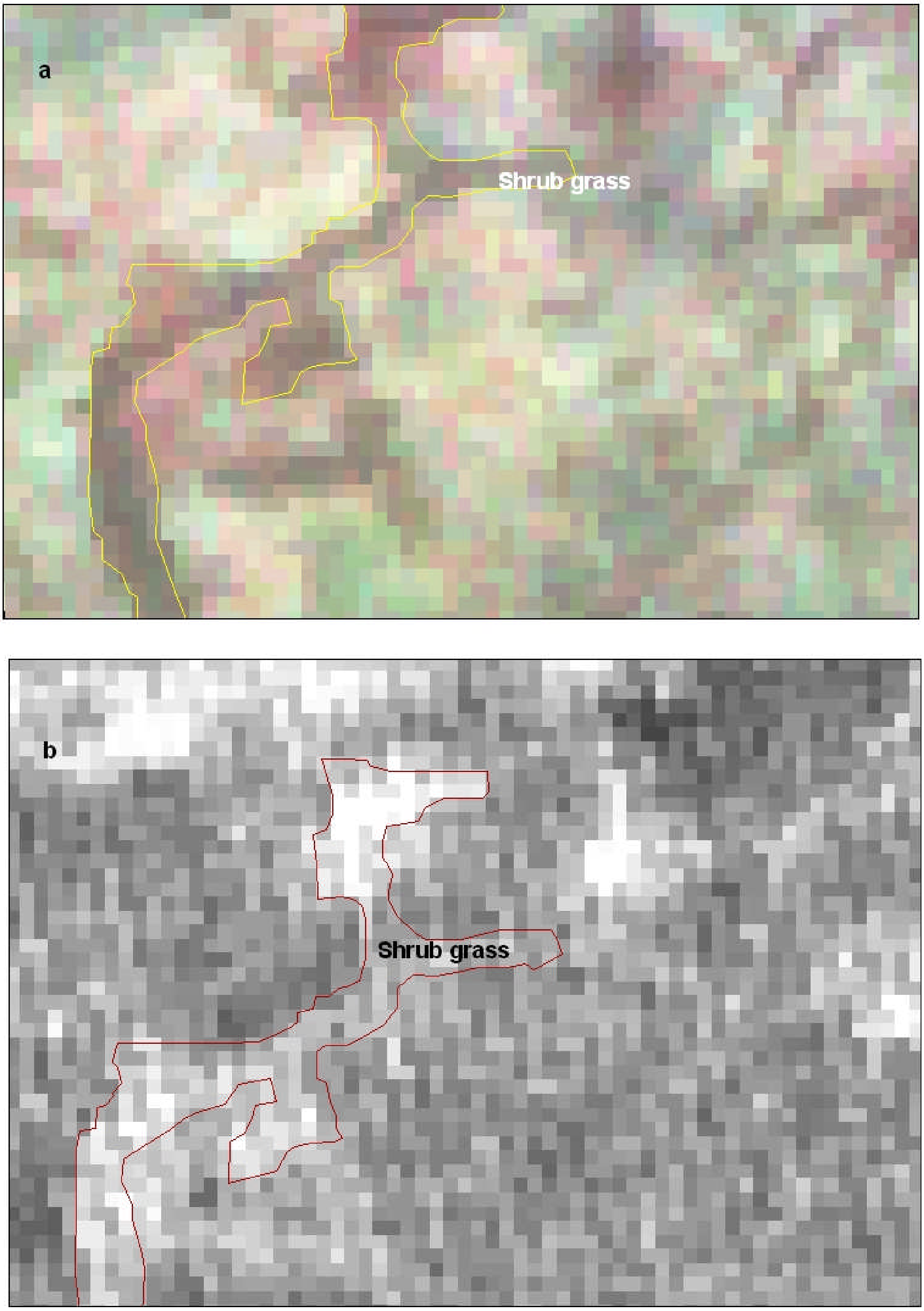


Figure 4-10: Illustration of a magnified image of the shrub grass category in the Landsat ETM+ image: a). wavebands 2, 3, 4 false colour composite, b). NDVI image

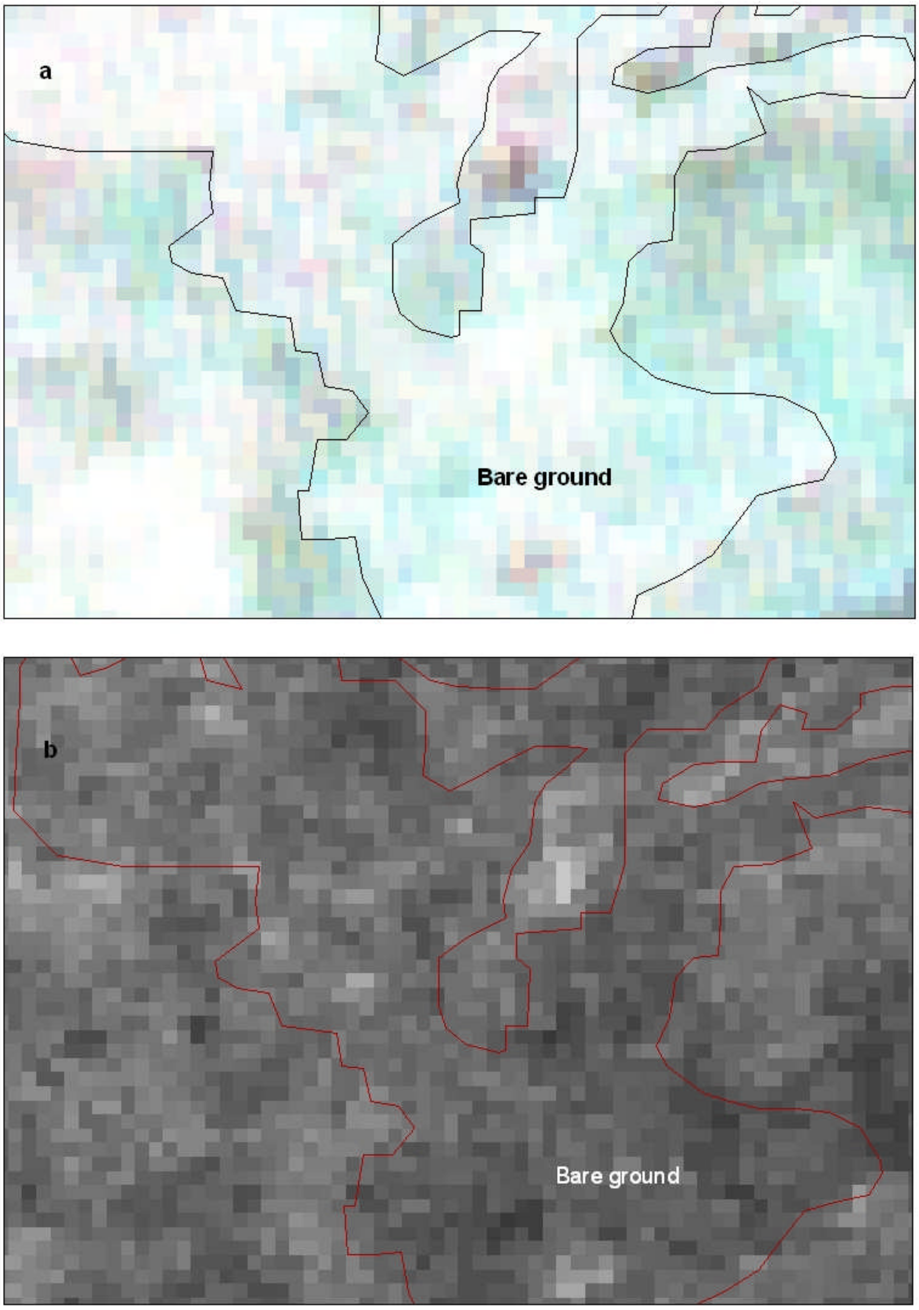


Figure 4-11: Illustration of a magnified image of the bare ground category in the Landsat ETM+ image a). wavebands 2, 3, 4 false colour composite, b). NDVI image

4.2.6 The interpretation

Having developed the keys for the interpretation, the 50 sample squares were each interpreted systematically on the 1986 and 2000 images as follows:

1. The easier and more recognisable classes were interpreted first and were subsequently used as a basis for the interpretation of the other classes. This applied to the urban area in sample square 28, the tree category in sample squares 6, 7, 8, 11, for example.
2. The tonal differences between the land cover classes in the red-green-blue (RGB) composite and NDVI images of 2005 were observed. The visual relationships identified were transferred to similar bands in the 2000 and 1986 images.
3. The sample squares that had similar shapes and patterns of land cover features in 2000 and 1986 similar to the 2005 were initially considered to be areas that were likely to have remained unchanged over the time period. Such areas were then matched up against the interpretation key characteristics to confirm whether they had changed or not.
4. In cases where the interpretation was difficult and category assignment of a feature could not be done with confidence, for example, identifying whether a feature belonged to the tree, shrub or bare ground categories because the feature did not conform to any of the interpretation key descriptions directly, an unsupervised classification of the image was used to aid the interpretation. The unsupervised classes so produced generally tallied with areas already known, and thus by using the unsupervised method the features that were difficult to identify were more easily allocated to the classification classes.
5. Although water was not classified in 2005, it was known that water was present in the Fadama, for example, during the field survey wet clay areas were encountered. Thus the unique appearance in the area encountered in the field with such characteristics was considered to be water. The area appeared blue in the RGB colour image and black in the NDVI, and was also different from its neighbourhood (Figures 4-12 and 4-13). This was similar to the appearance of Lake Chad and other parts of the same river in the same Landsat ETM+ image (Figure 4-14).

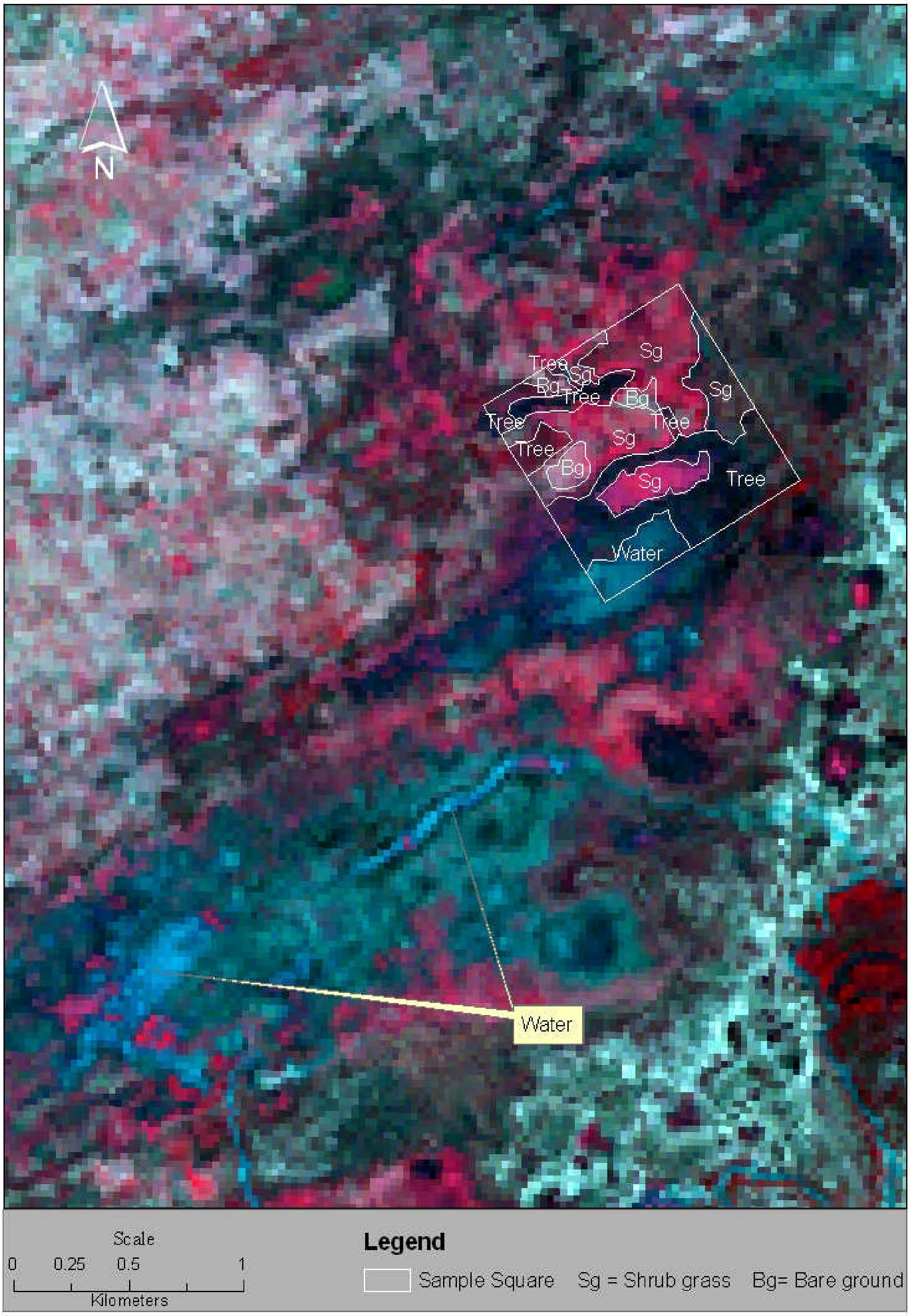


Figure 4-12: Indication of water bodies in the Landsat ETM+ image

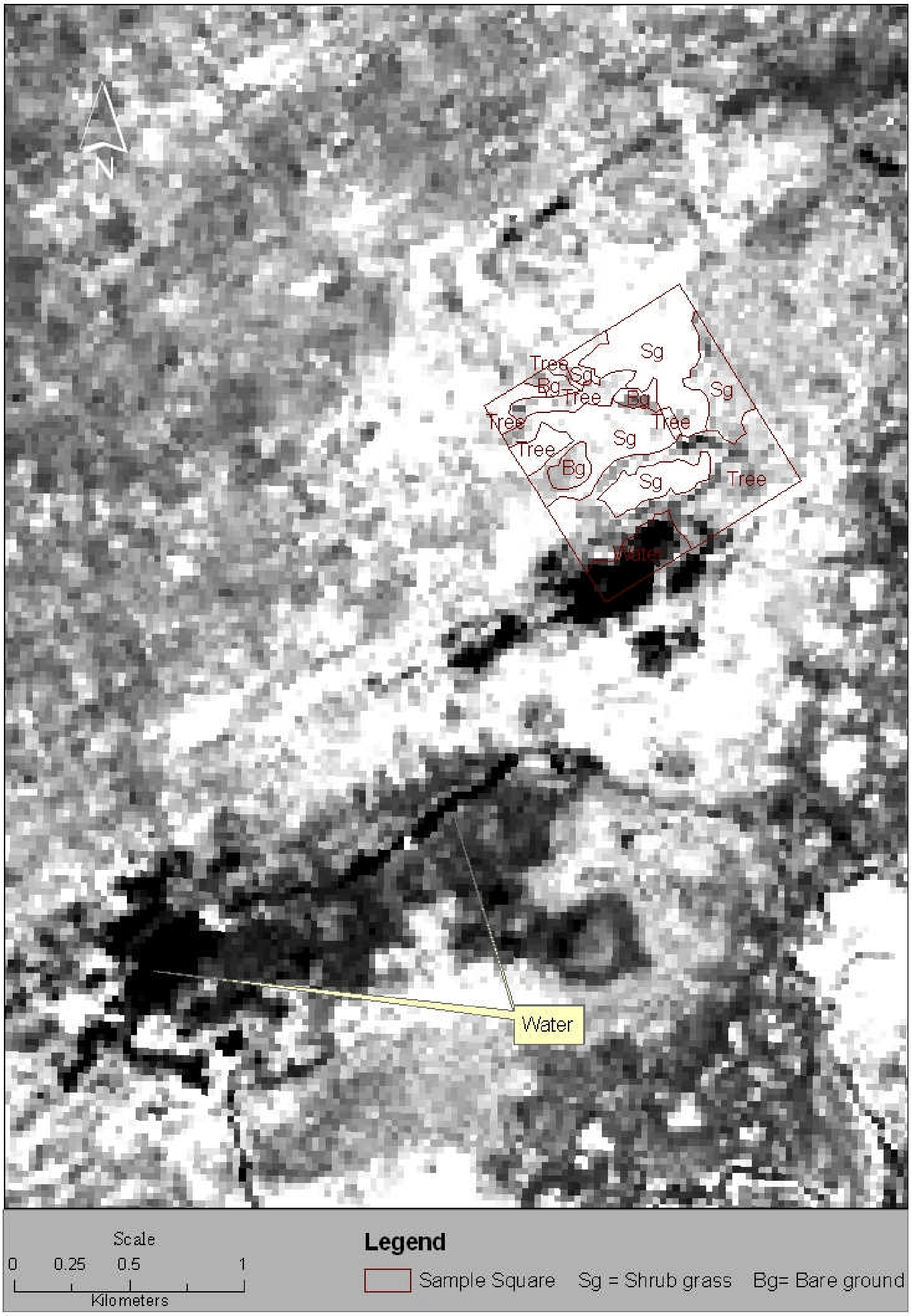


Figure 4-13: NDVI image of Landsat ETM+ (2000) with the darkest part indicating water

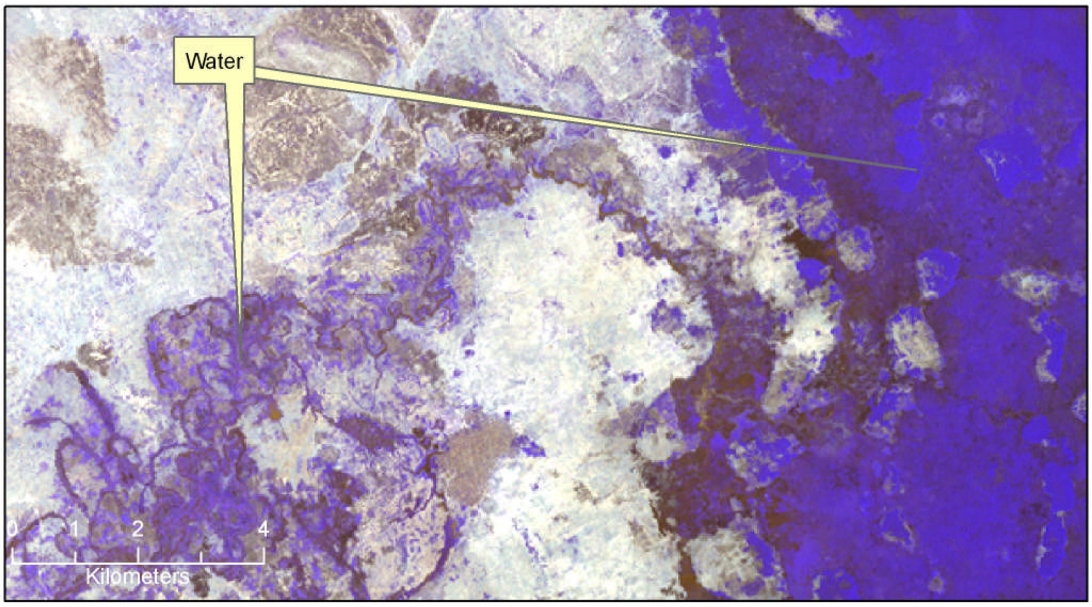


Figure 4-14: Illustration of the appearance of water in the Landsat ETM+ (2000) image for part of the River Yobe and Lake Chad

4.3 Classification of Landsat TM (1986) and ETM+ (2000)

The classifications were conducted using three wavebands equivalent to the NigeriaSat-1 imagery, that is, green 0.52 - 0.6µm, red 0.63 - 0.69 µm and near infrared 0.76 - 0.90 µm. These bands were selected in order to provide the same basis for the classification of all the images used for change detection. The Landsat ETM+ was acquired on 23rd October 2000 and the Landsat TM on the 9th October 1986. Both images were downloaded from Landsat.org and as orthorectified images to the same accuracy of 50m (specifications of the image data can be seen in Appendices A and B). Although these images were orthorectified, 8 points across each image were selected for verification. Landsat ETM+ was used as the reference image, and the points selected were compared on all three image dates and their root mean square error computed with results of 50m and 75m for NigeriaSat-1 and Landsat TM respectively. Since they were approximately of the same accuracy as the Landsat ETM+ (Appendix B) the geometry of the images was considered satisfactory.

The classification process is outlined below with the emphasis on the refinement of the training signatures and the classified result.

4.3.1 Training data

The use of unsupervised classification in the interpretation of the Landsat data motivated its use in the guided selection of pixels for training. In the case of the interpretation, the unsupervised classification was used to determine where potential land cover categories existed that were otherwise difficult to assign. The objective was to pick training pixels only from areas that had a clearly defined category. By this process mixed pixels (either pixels with a mixture of land cover categories or an anomalous pixel within a land cover due to the non homogeneity of a land cover) were not used in the training. This was similar to the process of refinement of the classification of the NigeriaSat-1 image (section 3.6.1).

The Landsat data was classified into 20 categories using the unsupervised classifier, and then compared to the reference data. The number 20 was chosen arbitrarily so that the range of the classes would potentially agree with the reference data categories. On comparison between the classified and reference data, classes 1, 2 and 3 related to the tree class; classes 7, 8, 9 and 10 related to the shrub grass class; and classes 16 to 20 to the bare ground class. The other classes were those that cut across the reference classes. The urban and the water classes did not dominate a particular range and hence were not considered in the process (illustrated in Figure 4-15). Pixels selected for training were only drawn from areas where the range of classes of the unsupervised classification agreed with the reference data.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Back ground	**Tree**			**Fuzzy Tree and Shrub-Grass**			**Shrub-Grass**				**Fuzzy Shrub-Grass and Bare ground**					**Bare ground**				

Figure 4-15: An illustration of the subdivision of the attributes from the 20 class unsupervised classification, showing the main classes and the fuzzy classes.

4.3.2 The Classification result and the accuracies of the Landsat TM and ETM+

The classification was conducted using the parallelepiped and maximum likelihood methods similar to that used to classify the NigeriaSat-1 image, which produced the land cover maps for the years 2000 and 1986 (Figures 4-16 and 4-17). Figure 4-16 shows that bare ground dominates most of the area in the Gamawa –Jakusko plain; the tree and the shrub in the Fadama; the bare ground and shrub grass in the Potiskum plain and tree dominates the Gudi-Jonga hills (Figure 1-4). These characteristics are also similar to the map of 1986 (Figure 4-17), with an increase in shrub grass in the north eastern corner of the study area. The classification of the Landsat ETM+ did produce some image artefacts in the north eastern and north western corner of the study area, for example the urban land cover was present in areas that were not urban.

Accuracy assessment was conducted based on randomly selected pixels across the sample squares (produced by the interpretation method above) independent of the pixels used for training the classifier. The overall accuracy of the 2000 map was 67% (Table 4-1) and for the 1986 map 71% (Table 4-2). Because few pixels were randomly selected for the water land cover it was not assessed well in the 2000 image and although few were selected in the 1986 map, it appears too few were selected to be used to make inferences. The producer and user accuracies of all the land covers were over 60% in the year 2000 except the shrub grass producer accuracy and the urban user accuracies. There was still high misclassification between the land covers. These classification accuracies were comparatively better than the classification of the NigeriaSat-1 image which was 61%.

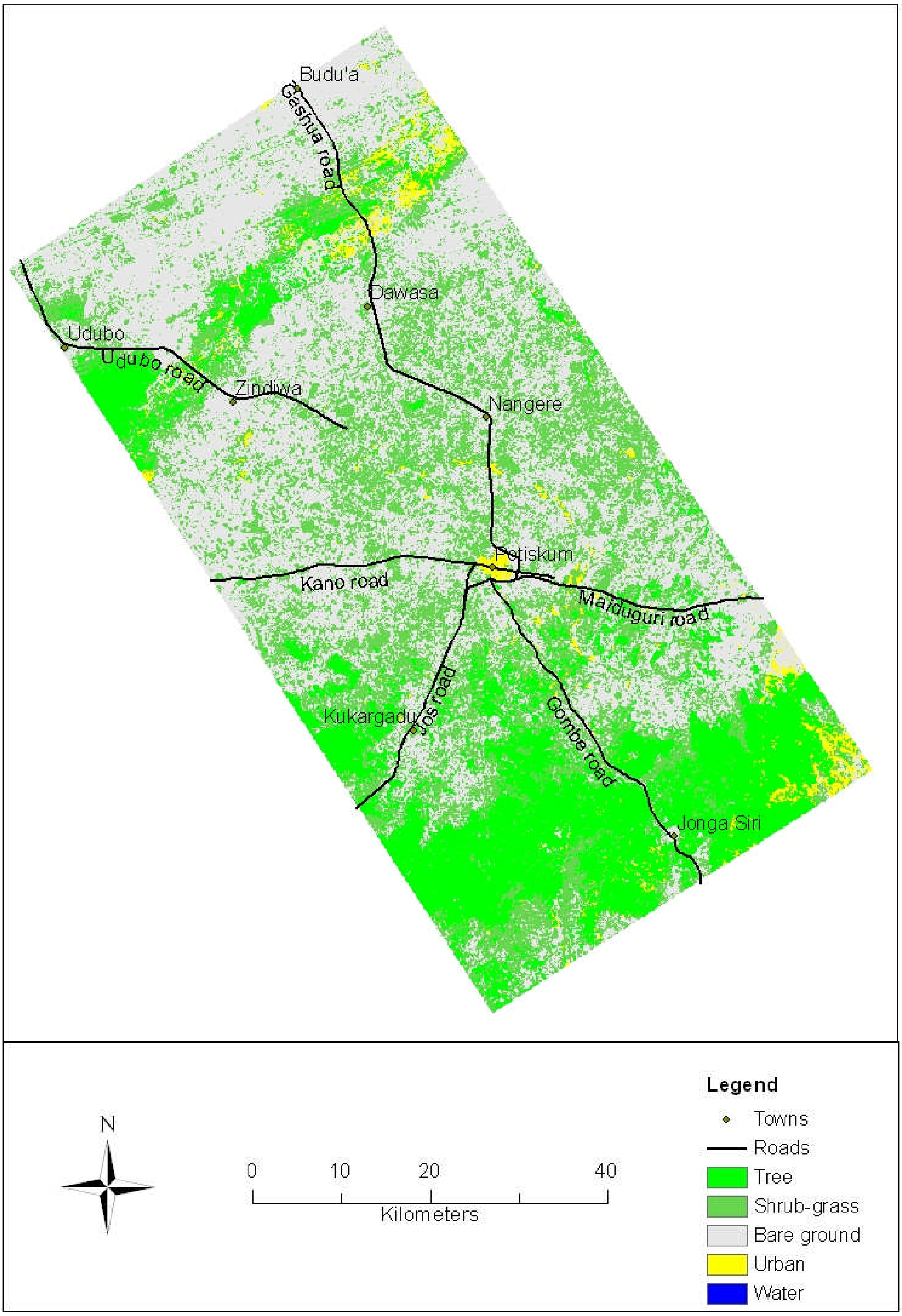


Figure 4-16: Land cover map for the year 2000 produced from Landsat ETM+ wavebands 2, 3, and 4

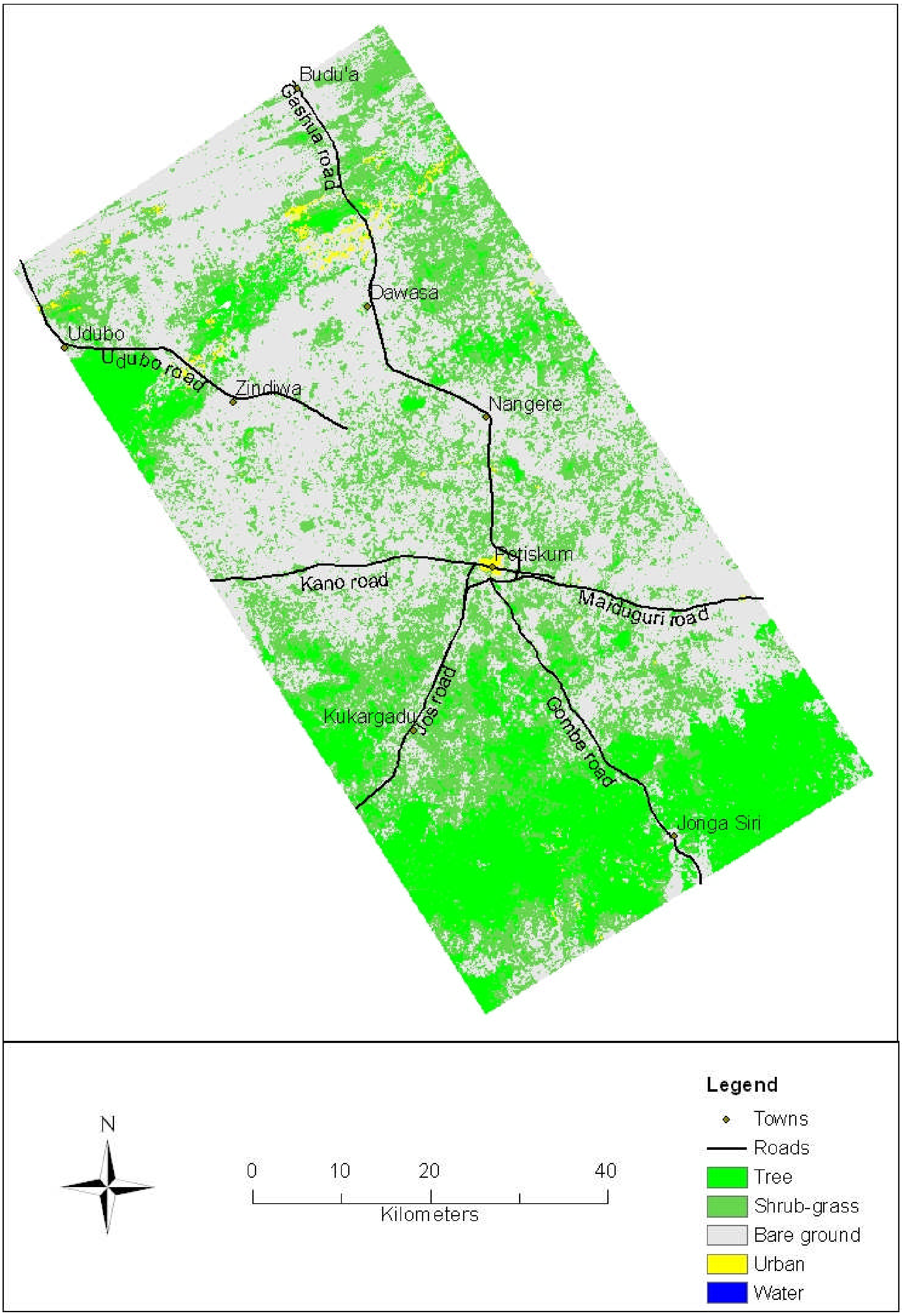


Figure 4-17: Land cover map for the year 1986 produced from Landsat TM wavebands 2, 3, and 4

Table 4-1: Confusion Matrix for the year 2000 classification

		Reference						
		Tree	Shrub grass	Bare ground	Urban	Water	Row Total	User Accuracy (%)
Classified	Tree	402	151	32	1	1	587	68.48
	Shrub grass	139	669	299	4		1111	60.22
	Bare ground	9	374	1184	4		1571	75.37
	Urban	7	23	75	61		166	36.75
	Water	4	4	5		0	13	0.00
	Column Total	561	1221	1595	70	1	3448	
	Producer Accuracy (%)	71.66	54.79	74.23	87.14	0.00		
Overall Accuracy (%)		67.17						
Kappa (%)		49.21						
Variance(kappa)		0.0002						

Table 4-2: Confusion Matrix for the year 1986 classification

		Reference						
		Tree	Shrub grass	Bare ground	Urban	Water	Row Total	User Accuracy (%)
Classified	Tree	505	164	29	3	3	704	71.73
	Shrub grass	99	693	436	9	1	1238	55.98
	Bare ground	5	259	1160	1		1425	81.40
	Urban	0	2	3	68		73	93.15
	Water	0	2			6	8	75.00
	Column Total	609	1120	1628	81	10	3448	
	Producer Accuracy (%)	82.92	61.88	71.25	83.95	60.00		
Overall Accuracy (%)		70.53						
Kappa (%)		54.78						
Variance(kappa)		0.0001						

4.4 Classification of Landsat ETM+ with the addition of the middle infrared wavebands

The middle infrared wave bands were added in order to test whether any significant differences were evident from the addition of the wavebands into the classification. This was in line with the objective of finding whether the lack of the middle infrared in the NigeriaSat-1 image was significant. The addition was undertaken in three ways: first, was to combine the two middle infrared wavebands, that is, bands 5 (1.55 -1.75 µm) and band 7 (2.08 – 2.35 µm) to the initial composite of bands 2, 3 and 4; secondly, band 5 only was added to composite, and finally band 7 only was added to the composite. All three combinations were classified into the land cover categories initially used for the standard composite image.

The summary of the accuracies is presented in Table 4-3, with the overall accuracies of 69% when the two wavebands were added, 68% when band 5 only was added and 71% when band 7 only was added. Band 7 appeared to be significantly different when the kappa was compared, however a chi square test showed no significance difference (as in section 3.7). Similar combinations were also applied to the Landsat TM image and produced accuracies of 68%, 70% and 72% for the addition of the two wavebands, band 5 only and band 7 only, respectively.

Comparison of the individual classes did not show any noticeable difference between the 3 combinations of the Landsat ETM+ with middle infrared and the classification without the middle infrared, except for the shrub grass class which had some slight changes in their values in all the three combinations. The producer accuracies for the tree, bare ground and urban did not show any appreciable change but the shrub grass slightly changed. However, the user accuracy of the urban category changed with the addition of the middle infrared from 37% to 78% when the two wavebands were added, and 54 % when band 5 alone was added and 42% when band 7 alone was added.

The addition of the middle infrared to Landsat TM in all types of combination decreased the producer's accuracies of the tree category by 10%, while it increased the shrub category by 11%. The tree category user's accuracy increased by about 10% when any of the combinations of the middle infrared was added. The water category increased in the producer accuracies in all combinations by 10%, and decreased in the user accuracies of the combination of the two middle infrared wavebands and of waveband 5 only by 5% (Tables 4-2 and 4-3). Other items of note in classifying with the middle infrared of the Landsat TM were that the addition of the combination of waveband 5 and 7 had lower accuracy than without the middle infrared, however, the addition of band 7 showed a better user's accuracy than all other tests. The user's accuracy of the Landsat TM waveband 7 closely relates to the geological sensitivity of the waveband, this was expected because of the types of building material used in the area.

In both Landsat TM and ETM+ there was no significant difference amongst their respective combinations of wavebands, except waveband 7 (by the kappa statistics). However there are slight variations in the producer and user accuracies. There was little change in the producer accuracies of the tree and shrub grass in the Landsat ETM+ using the middle infrared compared to the combination of wavebands without it. In a similar comparison the user accuracies of the urban category were greatly increased in the Landsat TM relative to what happened with the Landsat ETM+ comparison. In the comparison of classifications using the middle infrared, the user accuracies of the urban category in the Landsat ETM+ were lower than the Landsat TM. Comparing the addition of all the bands to either waveband 5 only or waveband 7 only shows that the user accuracy of the urban in Landsat ETM+ decreased compared to Landsat TM. Thus to select combinations that would improve the user accuracy of the urban category then the addition of both waveband 5 and 7 would be a better choice.

A visual difference was noticeable between the images produced by the classification with the combined middle infrared and those without especially within the urban land cover (Figures 4-18). The urban pixels that were erroneously visible in the Fadama were visibly reduced by the inclusion of the middle infrared bands. The appearance of the incorrect urban pixels in the Fadama varied according to the combination of the middle infrared bands (Figure 4-18, 4-19 and 4-20). Its effect on the classification of the urban land cover was not quite so obvious.

Table 4-3: Confusion matrix for classification of Landsat ETM+ and TM bands 2, 3, 4, 5 and 7

	Landsat ETM+		Landsat TM	
	Producer Accuracy (%)	**User Accuracy (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**
Bands 2,3,4,5 and 7				
Tree	**71.07**	**68.98**	**72.91**	**82.53**
Shrub grass	**58.02**	**58.69**	**73.45**	**56.23**
Bare ground	**75.11**	**75.87**	**69.41**	**83.21**
Urban	**87.14**	**78.21**	**84.51**	**90.91**
Water	**71.07**		**70**	**70.00**
Overall Accuracy (%)	**68.62**		**68.10**	
Kappa (%)	**50.69**		**50.45**	
Variance(kappa)	**0.0002**		**0.0002**	
Bands 2,3,4 and 5				
Tree	**71.43**	**68.49**	**73.73**	**80.90**
Shrub grass	**51.06**	**59.6**	**72.57**	**55.41**
Bare ground	**78.18**	**73.44**	**68.06**	**83.18**
Urban	**87.14**	**54.46**	**84.51**	**84.51**
Water			**70**	**70.00**
Overall Accuracy (%)	**67.63**		**70.88**	
Kappa (%)	**49.14**		**55.07**	
Variance(kappa)	**0.0002**		**0.0002**	
Bands 2,3,4 and 7				
Tree	**71.07**	**69.1**	**73.23**	**83.05**
Shrub grass	**57.61**	**60.38**	**72.39**	**56.26**
Bare ground	**74.29**	**76.3**	**70.45**	**82.64**
Urban	**87.14**	**41.78**	**81.69**	**96.67**
Water			**70.00**	**77.78**
Overall Accuracy (%)	**70.88**		**71.81**	
Kappa (%)	**55.07**		**56.22**	
Variance(kappa)	**0.0002**		**0.0001**	

Table 4-4: Kappa and Chi-square comparison of different waveband arrangements of the Landsat ETM+ and TM images

	Landsat ETM+				Landsat TM			
	b234	**b23457**	**b2345**	**b2347**	**b234**	**b23457**	**b2345**	**b2347**
Kappa z								
b234		**NS**	**NS**	**S**		**NS**	**NS**	**NS**
b23457	**0.74**		**NS**	**S**	**0.67**		**NS**	**NS**
b2345	**0.035**	**0.775**		**S**	**0.145**	**0.525**		**NS**
b2347	**2.93**	**2.19**	**2.965**		**0.72**	**0.05**	**0.575**	
Chi-square								
b234		**NS**	**NS**	**NS**		**NS**	**NS**	**NS**
b23457	**1.71**		**NS**	**NS**	**1.07**		**NS**	**NS**
b2345	**0.21**	**0.73**		**NS**	**0.1**	**0.52**		**NS**
b2347	**0.71**	**0.22**	**0.01**		**1.37**	**0.2**	**0.73**	

Note: b denotes waveband and the numbers indicate the waveband number forming the combination, S means statistically significant and NS not significant

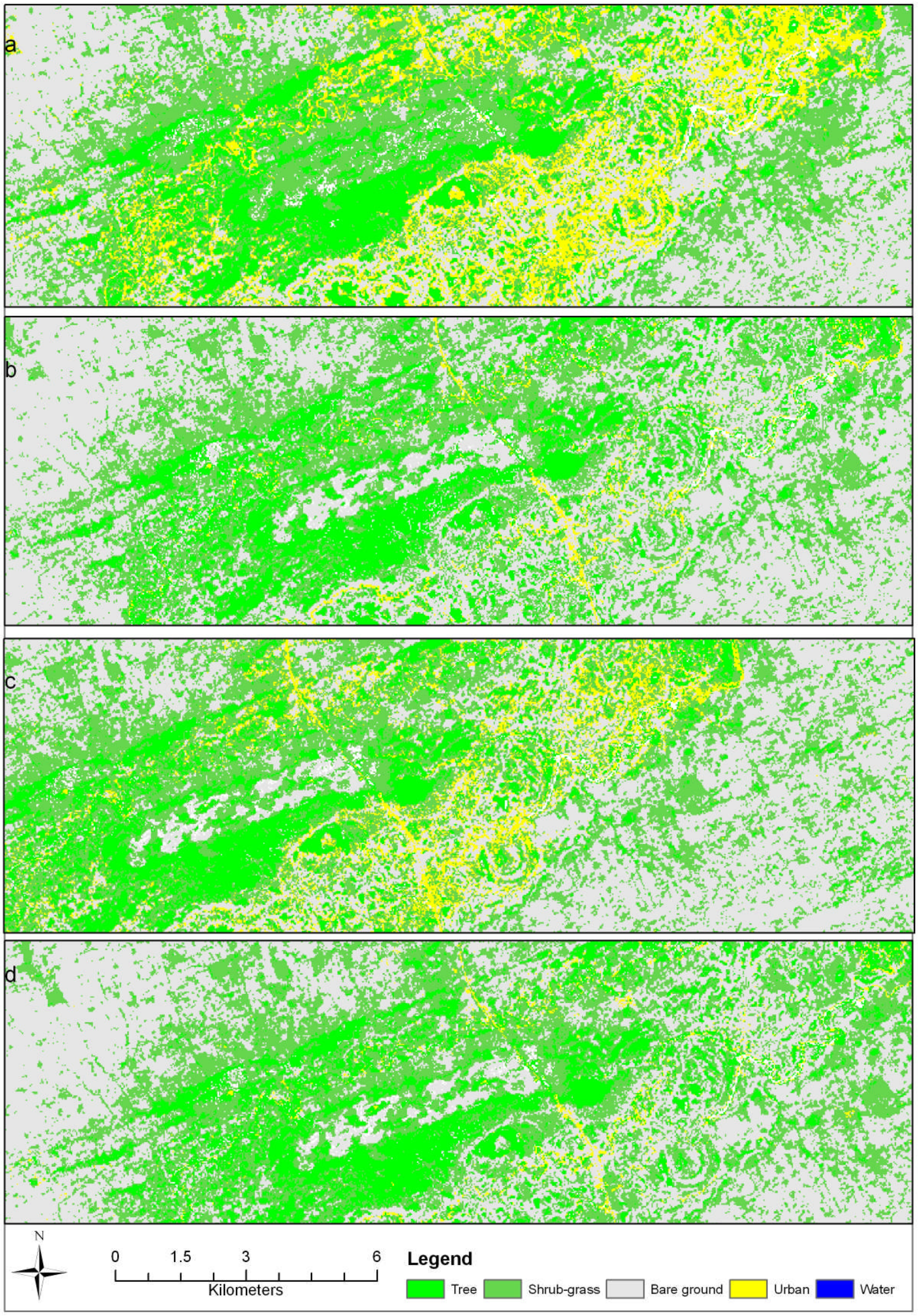


Figure 4-18: a and c are the classified Landsat ETM+ and TM image of the Fadama area without the middle infrared, c and d respectively included the middle infrared waveband 5. The urban land cover in the area was an error which the inclusion of the middle infrared reduced.

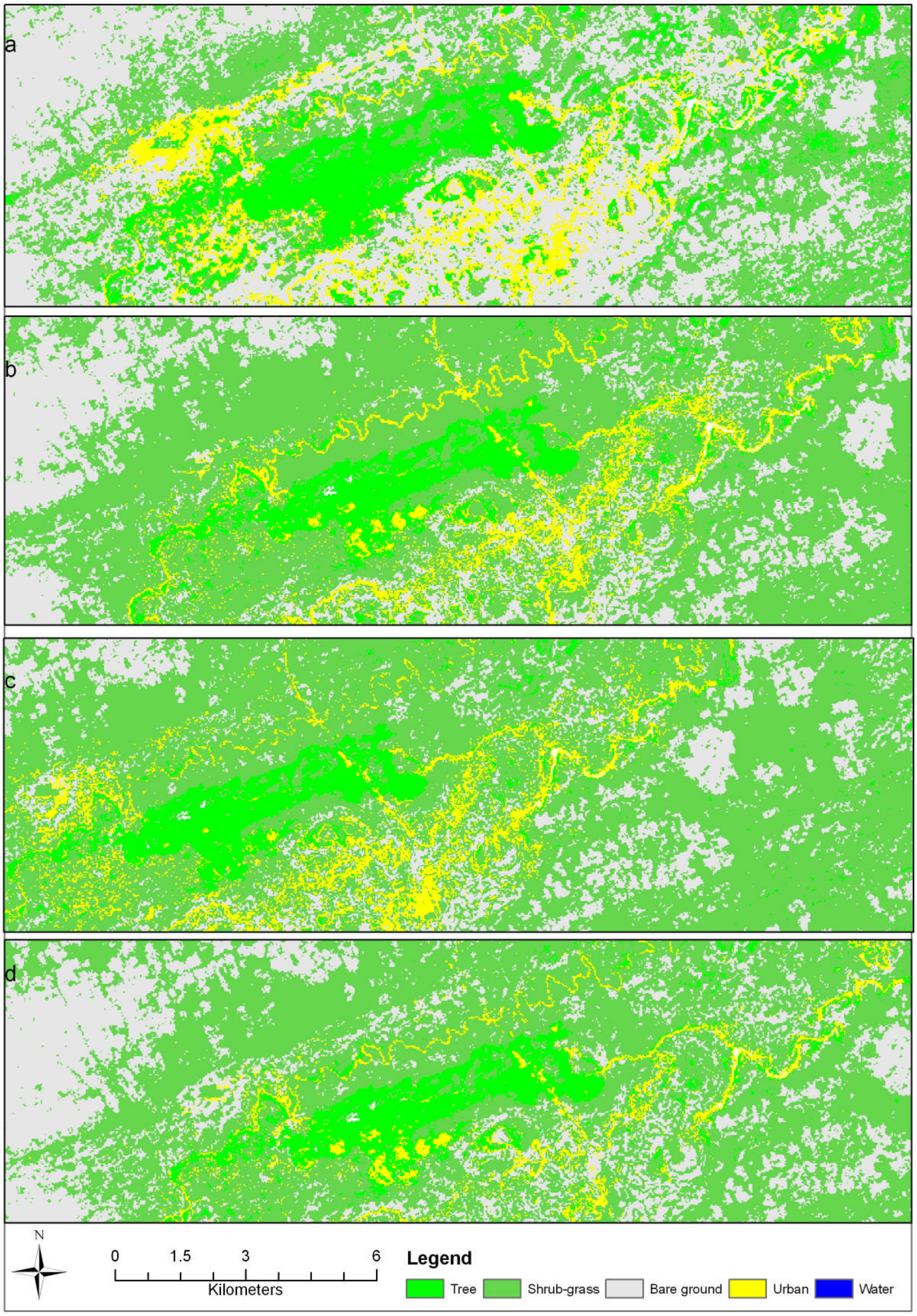


Figure 4-19: a and c are the classified Landsat ETM+ and TM image of the Fadama area without the middle infrared, c and d respectively include the middle infrared wavebands 5 and 7. The urban land cover in the area was an error which the inclusion of the middle infrared reduced.

Figure 4-20: Effect of middle infrared on urban land cover a). classified Landsat ETM+ wavebands 2,3,4; b). classified Landsat ETM+ wavebands 2,3,4,5; c). classified Landsat ETM+ wavebands 2,3,4,7; d). classified Landsat ETM+ wavebands 2,3,4,5,7; e). classified Landsat TM wavebands 2,3,4; f). classified Landsat TM wavebands 2,3,4,5; g). classified Landsat TM wavebands 2,3,4,7; h). classified Landsat TM wavebands 2,3,4,5,7

4.5 The implication of adding the middle infrared to the quality assessment of the NigeriaSat-1 image

The result of the comparison of the classifications with and without the two middle infrared wavebands showed no significant differences (Table 4-4). Although the confusion matrix analysis indicated no significant difference the visual comparison did indicate that the addition did enhance the classification of the urban category and reduced the misclassification of other classes to urban. This implies that adding the middle infrared to the NigeriaSat-1 sensor may not contribute much to bettering classification accuracy of land cover in the north eastern part of Nigeria during the dry season. This however does not include the aspect of geological studies and soil moisture for which the middle infrared are useful (Jensen, 2000; Wilson and Sader, 2001). Since the images used in this analysis were from the dry season it is possible that conducting the analysis for a wet season image (in which the water content of both the soils and vegetation have increased) would lead to a different result. This possibility is due to the presence of soil moisture and the difference in the water absorption of various soils and vegetation in relation to the middle infrared reflectance (Boyd and Petitcolin 2004; Yang et al., 2003; Boyd and Petitcolin 2004; Boyd and Petitcolin 2004, Panigrahy and Parihar 1992). This possibility also applies to the wetter parts of Nigeria, hence the application of the middle infrared in the southern part of Nigeria could lead to better discrimination of soil and vegetation.

4.6 Summary of the classification of Landsat ETM+ and TM

The classification of Landsat ETM+ (2000) and TM (1986) was undertaken in a similar way to the classification of the NigeriaSat-1 image. Image interpretation techniques were applied to develop reference data for both years. The image interpretation procedure first used the characteristics of the land covers in the NigeriaSat-1 classification: these included their tonal relationship, overall patterns of a land cover in relation to its neighbourhood and personal knowledge to establish keys for interpretation. The keys were used together with the earlier procedure to interpret areas covered by the fifty field survey sample squares.

Spectral signatures were developed from the interpreted areas. The tree, shrub grass and bare ground signatures were refined using an unsupervised based filter. The filter ensured that signatures defining a particular land cover were from the same range defined by the unsupervised classification and avoided areas that would give rise to spectral confusion.

Classifications of the two images were undertaken which produced two maps and two confusion matrices with overall accuracies of 67% and 71% considered good for change assessment. The classification was first undertaken with the three bands similar to the NigeriaSat-1 and then by the addition of the two middle infrared bands, this was to provide the basis for the analysis of the NigeriaSat-1 image. The addition of the infrared did not significantly improve the overall accuracies of the classification although there was visual improvement of the classification of the urban pixels.

Chapter 5 Land Cover Change Analysis

5.1 Introduction

The maps produced from the classification of satellite images from 1986, 2000 and 2005 were used to answer the question as to whether land cover changes had taken place. If there were changes, what were their quantities and the distribution of the changes and what were the uncertainties associated with the estimation of the type and amount of change. Also, because of the variation in the landform, environmental disturbance such as drought, desertification, wind erosion and the impact of the growth of urban areas like Potiskum, this work sought to answer the question as to whether there were variations in the intensity of changes across the study area.

The change analysis was based on maps that have notable errors (Tables 3-14 and 4-1) which was not unusual for maps produced by a similar methodology, for example, Abdalla (1994), Lawan (1996), Sannier (2000), Foody (2002) and Foody (2006). These errors were transferred into the change analysis (Coppin et. al 2004; Congalton and Green, 1999) and thus there was a need to analyse and describe the errors, which may also be used to improve the estimates of the land cover areas (van Oort, 2005; Pontius and Lippitt 2006; Bird et al., 2000).

This chapter has five sections: the first describes an overview of the methods used in analysing the changes and their errors; the second section provides the summary estimation of the land cover areas and the changes; the third, describes the changes of each land cover according to regions and location of intensive change; the fourth, describes the perception of environmental changes in the study area; the fifth, analyses errors in the change analysis; the sixth, summarises important characteristics of the changes.

5.2 Methodology for land cover change analysis

The methodology had three components, which were: a description of the changes, analysis of the errors in the changes evident, and a method to improve the accuracy of the estimation of the changes. Figure 5-1 shows an overview of the methodology. One component of the analysis of change was the description of change in terms of loss, gain and gross change in the land cover between the three mapping dates. Another component of the change analysis methodology undertook a more elaborate analysis by considering the initial state of the land cover and its status at the second and third dates thus producing both a map of change and a summary of transition of land cover of the two periods and presented as a transition matrix. The map of change was used to identify the locations of intensive change, and by using a regional change density the differences according to the regions were distinguished. Confusion matrices were used to analyse the errors contained within the mapping and from these to construct transition error matrices, and these were the basis for describing the errors used to improve change estimation.

Land change maps for individual land covers were produced and analysed individually according to regional distribution and regional change density. Both the transition matrix and transition error matrix were used to produce adjusted estimates of land cover areas.

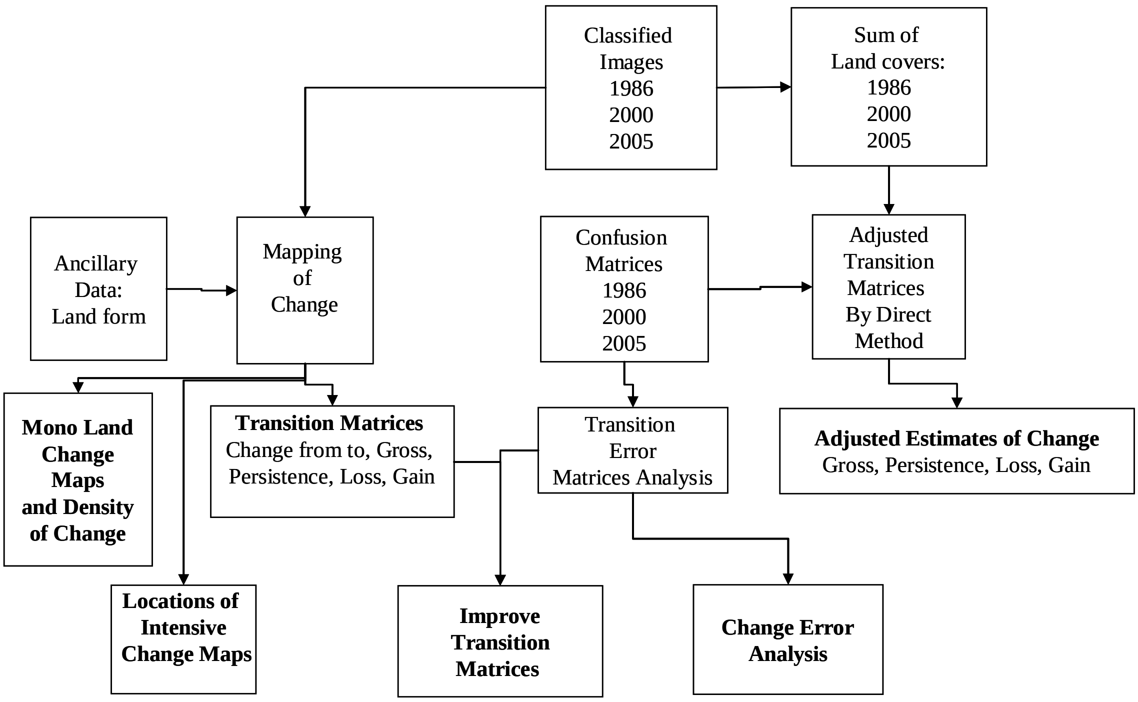


Figure 5-1: Overview of the methodology for the land cover change analysis

5.2.1 Description of the methodology of land cover change

A simple form of description of changes in the five land cover types can be derived from the sum of each of the land covers at each of the dates of imagery and thus estimating the change from their differences. This simple form of analysis is similar to the form in which many land cover data are supplied (van Oort, 2007). The difference between the estimates of a land cover can be net loss or net gain, that is, the difference in the quantity of the land cover in a year compared to a preceding year. For example, the difference in tree land cover in 2000 and that of 1986 will be a net loss if negative, meaning there was more of the land cover in the preceding year, and a net gain with a positive difference. However this simple description does not indicate the transition properties of the change, for example, it does not identify how much of the tree area remained tree or changed to shrub grass, or the shrub grass area in the preceding year that became tree.

In order to define changes in terms of the status at various dates and their spatial variation a 'Combinatorial And' tool was used in the ArcGIS software package. This produced both maps of change and the basis for estimating the transition of the land covers and these estimates were presented in a transition matrix. The maps of change for 1986 to 2000 and from the 2000 to 2005 were created by applying the Combinatorial-And tool (steps 1 and 2, in Box 5-1), and were subsequently related to the physiographic regions of the study area according to transition categories (Step 3, Box 5-1). The transition categories had seven distinct single and combinations of states of the land covers between the three mapping dates. The transition maps produced by this step were maps of individual land cover containing every pixel that had changed or not over the three time periods. For example the tree transition map had every pixel that had been tree in 1986, 2000 and 2005 which had or had not changed.

Box 5-1: The steps followed to create change maps

Legend:
$Class_i$ = Tree, Shrub grass, Bare ground, Urban, or Water
t_i = Year (1986, 2000 or 2005)
Region $_i$ = Gamawa-Jakusko plain, Fadama, Potiskum Plain, Gudi-Jonga hills)
Process:
Step 1: Combinatorial_ And_1 (1986_{class}, 2000 $_{class}$)
Step 2: Combinatorial_ And_2 ((Combinatorial_ And_1 (1986_{class}, 2000 $_{class}$), 2005 $_{class}$)
Step 3: Combinatorial_ And (Class $_i$, Region) to produce the following transition categories
a. $Class_i$ at 2005 0nly
b. $Class_i$ at 2000 0nly
c. $Class_i$ at 2000 and 2005 0nly
d. $Class_i$ at 1986 0nly
e. $Class_i$ at 1986 and 2005 0nly
f. $Class_i$ at 1986 and 2000 0nly
g. $Class_i$ at 1986, 2000, 2005 0nly

A transition matrix (Pontius and Cheuk, 2006; Pontius et. al., 2004; Braimoh, 2006) is a representation of land cover classes in one year against the classes in another. A generalised form of a transition matrix is illustrated in Table 5-1. Classes 1, 2, 3 and 4 are the land cover classes in the two years with quantities aij. The quantities along the row are components of a class in year A and along the column for year B. The values along the diagonal a_{ii} are the quantities that have remained the same between the two years, that is, they are classes that show persistence (Pontius et al., 2004). The off diagonal elements a_{ij} are those that have changed from year A to B. The difference in the sums of the same class in the two years is either a net gain or net loss of the class, thus a_{+1} - a_{1+} is the net change in Class 1. Where it is negative then the land cover had lost area and positive the class had gained in area.

Table 5-1: Illustration of a transition matrix

	Year B					
	Class1	**Class 2**	**Class 3**	**Class 4**	**Total Year A**	**Loss**
Year A						
Class 1	a_{11}	a_{12}	a_{13}	a_{14}	a_{1+}	a_{1+}-a_{11}
Class 2	a_{21}	a_{22}	a_{23}	a_{24}	a_{2+}	a_{2+}-a_{22}
Class 3	a_{31}	a_{32}	a_{33}	a_{34}	a_{3+}	a_{3+}-a_{33}
Class 4	a_{41}	a_{42}	a_{43}	a_{44}	a_{4+}	a_{4+}-$a4_4$
Total Year B	a_{+1}	a_{+2}	a_{+3}	a_{+4}		
Gain	a_{+1}-a_{11}	a_{+2}– a_{22}	a_{+} –a_{33}	a_{+4}–a_{44}		

The computation of net change may hide the swapping that can occur when a certain quantity of a land cover is lost in one location but gained in another location, this can be computed by Equation 5-1 (Pontius et al., 2004).

$$S_j = 2 \times \min(a_{+j}-a_{jj},\ a_{j+}-a_{jj}) \qquad \textbf{Equation 5-1}$$

Pontius et al. (2004) suggest that the interpretation of change between land covers should consider that changes could be partly random (i.e. expected change) or systematic (that is, a change other than random that could have occurred due to the effect of the size and the persistence of the land cover category). Because the persistence of land covers is often large, Pontius et al (2004) reason that the persistence should be accounted for in the analysis. In order to estimate random changes that could occur, they used chi-square analysis to assume that the expected value would be equal to the random value. Thus random change was computed from the expected value. They calculated the expected value by assuming that the gain of a land cover at the second year (when analysing changes between two years) was expected to have risen proportionately from each of the land covers in the previous year, this was expressed as Equation 5-2 and Equation 5-3 for the analysis of loss.

$$G_{ij} = a_{+j} - a_{jj}\left(\frac{a_{i+}}{\sum_{i=1,i\neq j}^{j} a_{i+}}\right) \qquad \textbf{Equation 5-2}$$

$$L_{ij} = a_{i+} - a_{ii}\left(\frac{a_{+j}}{\sum_{i=1,j\neq i}^{j} a_{+j}}\right) \qquad \textbf{Equation 5-3}$$

The random values computed from the equations could determine whether the actual transition value between land covers differed from its expected value. If the magnitude of the difference was low then the transition was weak, meaning there was a high chance that the change was more random than systematic (Pontius et al., 2004).

5.2.2 The elements of land cover change analysis

Below are the main elements of land cover change analysis described above and applied in the next section:

Net loss: when the difference between the area of a land cover in a year and the preceding year was negative.

Net gain: when the difference between the area of a land cover in a year and the preceding year was positive.

Persistence: the area of a land cover that remained unchanged between the two years

Loss: this is the difference between the area of a land cover in the first year less the area that persisted between the two years being analysed.

Gain: this is the difference between the area of a land cover in the second year less the area that persisted between the two years being analysed.

Swap: is the area of a land cover loss in the first and gained in the second.

Absolute net change: this the absolute difference between loss and gain.

Actual value: the value of a land cover.

Expected value: the value of a land cover expected based on chi-square computation.

5.3 The land cover changes

In this section land cover changes are analysed from a general perspective by looking at each of the land cover categories and their transition (after Pontius et al., 2004). From the classification results (Chapters 3 and 4), the area of each of the land covers was computed. The percentage gross change, that is, the sum of the net changes from 1986 to 2000, was 8% and between 2000 and 2005 4% (Table 5-2). The shrub grass category had a net loss of 7% between 1986 and 2000.

The transition matrices for 1986 to 2000 and 2000 to 2005 are presented in Tables 5-3 and 5-4 in hectares and 5-5 and 5-6 in percentage of the study area. This was computed for each land cover for each pair of time periods. The area of the land covers that did not change, that is, those that persisted (given by the sum of the diagonal) between 1986 and 2000, was 309,530 ha or 61% of the study area (Tables 5-3 and 5-5) and between 2000 and 2005 was 322,813 ha or 64% of the study area (Tables 5-4 and 5-6).

The analyses of persistence, loss, gain and swaps that occurred between pairs of classifications for the two dates were done with the aid of Tables 5-5 and 5-6. Each table has three sections: the first section presents a general analysis that had the actual transition matrix transformed into percentage of the study area, computed from the gain, loss, swap and absolute change (described in section 5.2.1). The second section presents the gain analysis which involved the computation of the expected gain (Equation 5-2), the difference between the observed and the expected, and the proportion of the difference to the expected, that is, the observed minus the expected divided by the expected, a kind of Chi-square. The third section presents the loss analysis (Equation 5-3) which is a reverse of the gain analysis. The analysis of gain and loss was focussed on the effect of the persistence of the changes (Pontius et al., 2004).

In Table 5-2, changes in land cover was presented in terms of net loss and gain as the differences in the areas of the land covers at the end of the second year of classification. In Tables 5-5 and 5-6 the loss was considered as the difference between the total of a land cover less the unchanged portion between the two years, and gain as the total in the second year less the unchanged portion. These quantities are both presented in the transition matrices (Tables 5-5 and 5-6) and interpreted thus: between 1986 and 2000 15% of the study area is tree land cover that did not change between 1986 and 2000 and 13% between 2000 and 2005. There was 5% which was gained over what persisted by 2000 and 6% loss from what persisted in 1986 and thus a net change of 1%. There was a swap of 10% in tree in the same period i.e. 5% loss of tree in 1986 was gained in different locations in 2000. Similar interpretations for shrub grass, bare ground and urban indicated a persistence of 14%, 32% and 0.5, respectively, and a swap of 28%, 22% and 2%. The persistence of tree and shrub grass decreased in 2000 - 2005 compared to 1986 - 2000 but increased for bare ground and urban in the same comparison. Similarly the swap for 2000 – 2005 reduced compared to 1986 – 2000 for the tree and urban but increased for the shrub and the bare ground.

The expected shrub grass in 1986 that became tree in 2000 was 2.1% of the study area while the actual was 3.8% (Table 5-5). This indicated that changes from the shrub grass to tree were more than random, meaning it couldn't have occurred by chance or error because of the size of the shrub grass area. The bare ground in 1986 that became tree in 2000 was more likely to be random than actual. The urban area that became tree was 0.3% of the study area. However, it was estimated to be 0.1% thus the change was probably more than random. The expected loss of shrub grass that was gained by tree was less than the actual and similarly the expected loss of the shrub grass to bare ground was less. Similar interpretation could be made for shrub grass, bare ground and urban. The water category was left out of the analyses because its quantity was too small. The expected values for shrub grass in 1986 becoming bare ground in 2000, and bare ground in 1986 becoming shrub grass in 2000 were 10% and 9%, respectively.

The interpretation of the gain and loss analyses (Tables 5-5 and 5-6) in accordance to Pontius et al. (2004) indicated that when tree gains it replaces shrub grass and urban but not bare ground and when it incured losses it was replaced by shrub grass and urban but not bare ground; when shrub grass gains it replaces bare ground but not tree, it does replace urban between 2000 and 2005 but not between 1986 and 2000; when bare ground gains it does not replace the tree and not urban between 1986 and 2000 but replaces shrub ground, and when it incurred losses it was replaced by bare ground and urban; the gain by urban replaces tree only between 1986 and 2000 and replaces both tree and shrub grass between 2000 and 2005 and when it incurred losses it was replaced by both tree and shrub grass but not bare ground.

Table 5-2: Area of land covers computed from pixel counting for the years 1986, 2000 and 2005

	Area (ha)			**Change 1986-2000 (ha)**		**Change 2000 to 2005 (ha)**	
	1986	**2000**	**2005**	**Net Loss**	**Net Gain**	**Net Loss**	**Net Gain**
Tree	**108,493**	**100,782**	**83,852**			**16,930 (3.35)**	
	(21.47)	**(19.95)**	**(16.6)**	**7,711 (1.53)**			
Shrub-	**172,595.2**	**138,625**	**150,142**	**33,970**			**11,517**
Grass	**(34.16)**	**(27.44)**	**(29.72)**	**(6.72)**			**(2.28)**
Bare	**217,807.5**	**246,766**	**253,982**		**28,959**		**7,215**
ground	**(43.11)**	**(48.84)**	**(50.27)**		**(5.73)**		**(1.43)**
Urban	**6,158.61**	**18,239**	**17,268**		**12,081**	**972 (0.19)**	
	(1.22)	**(3.61)**	**(3.42)**		**(2.39)**		
Water	**190.08**	**831**			**641 (0.13)**	**831 (0.16)**	
	(0.04)	**(0.16)**					
Gross Change				**41,681 (8.25%)**		**18,736 (3.71%)**	

Note: The figures in brackets are the percentage equivalent.

Table 5-3: Land cover transition matrix 1986 to 2000 in hectares

	1986↓					
2000→	Tree	Shrub grass	Bare ground	Urban	Water	Total (2000)
Tree	76,252	19,209	3,801	1,441	79	100,782
Shrub grass	19,392	68,781	49,044	1,394	14	138,625
Bare ground	7,554	76,181	162,111	909	11	246,766
Urban	4,818	8,227	2,821	2,337	37	18,239
Water	477	198	31	77	49	831
Total (1986)	108,493	172,595	217,807	6,159	190	505,244

Table 5-4: Land cover transition matrix 2000 to 2005 in hectares

	2000↓					
2005→	Tree	Shrub grass	Bare ground	Urban	Water	Total (2005)
Tree	67,868	10,600	2,456	2,602	325	83,852
Shrub grass	20,608	65,999	58,200	5,107	229	150,142
Bare ground	7,175	57,911	183,574	5,158	165	253,982
Urban	5,132	4,116	2,536	5,372	112	17,268
Water						
Total	100,782	138,625	246,766	18,239	831	505,244

Table 5-5: Actual and expected land cover transition matrix 1986 to 2000 expressed as a percentage of the total study area

	2000↓					
1986→	Tree (%)	Shrub grass (%)	Bare ground (%)	Urban (%)	Total (1986) (%)	Loss (%)
<u>General analysis</u>						
Actual value						
Tree	15.1	3.8	1.5	1	21.4	6.3
Shrub grass	3.8	13.6	15.1	1.6	34.1	20.5
Bare ground	0.8	9.7	32.1	0.6	43.2	11.1
Urban	0.3	0.3	0.2	0.5	1.3	0.8
Total (%)	20	27.4	48.9	3.7	100	100
Gain	4.9	13.8	16.8	3.2		
Swap	9.8	27.6	22	1.6		
Absolute Net Change	1.4	6.7	5.7	2.4		
<u>Gain Analysis</u>						
Expected (Random) Value						
Tree	15.1	4.5	6.3	0.7		
Shrub grass	2.1	13.6	10.1	1.1		
Bare ground	2.7	7.5	32.1	1.4		
Urban	0.1	0.3	0.4	0.5		
Difference between Actual and Expected						
Tree	0.0	-0.7	-4.8	0.3		
Shrub grass	1.7	0.0	5.0	0.5		
Bare ground	-1.9	2.2	0.0	-0.8		
Urban	0.2	0.0	-0.2	0.0		
Difference divided by Expected						
Tree	0.0	-0.2	-0.8	0.4		
Shrub grass	0.8	0.0	0.5	0.4		
Bare ground	-0.7	0.3	0.0	-0.6		
Urban	2.7	0.1	-0.5	0.0		

Table 5-5 Continued

	2000↓			
	Tree (%)	**Shrub grass (%)**	**Bare ground (%)**	**Urban (%)**
1986→				
Loss Analysis				
Expected (Random) Value				
Tree	**15.1**	**2.2**	**3.9**	**0.3**
Shrub grass	**5.6**	**13.6**	**13.8**	**1.0**
Bare ground	**4.3**	**6.0**	**32.1**	**0.8**
Urban	**0.2**	**0.2**	**0.4**	**0.5**
Difference between Actual and Expected				
Tree	**0.0**	**1.6**	**-2.4**	**0.7**
Shrub grass	**-1.8**	**0.0**	**1.3**	**0.6**
Bare ground	**-3.5**	**3.7**	**0.0**	**-0.2**
Urban	**0.1**	**0.1**	**-0.2**	**0.0**
Difference divided by Expected				
Tree	**0**	**0.7**	**-0.6**	**3.6**
Shrub grass	**-0.3**	**0**	**0.1**	**2.2**
Bare ground	**-0.8**	**0.6**	**0**	**0.5**
Urban	**1.1**	**10.5**	**-0.4**	**0**

Table 5-6: Actual and Expected Land Cover Transition Matrix 2000 to 2005 as a percentage of the total study area

	2005↓					
	Tree (%)	**Shrub grass (%)**	**Bare ground (%)**	**Urban (%)**	**Total (1986) (%)**	**Loss (%)**
2000⟶						
Actual Value						
Tree	**13.4**	**4.1**	**1.4**	**1**	**19.9**	**6.5**
Shrub grass	**2.1**	**13.1**	**11.5**	**0.8**	**27.5**	**14.4**
Bare ground	**0.5**	**11.5**	**36.3**	**0.5**	**48.8**	**12.5**
Urban	**0.5**	**1**	**1**	**1.1**	**3.6**	**2.5**
Total	**16.5**	**29.7**	**50.2**	**3.4**	**99.8**	
Gain	**3.1**	**16.6**	**13.9**	**2.3**		
Swap	**6.4**	**28.8**	**25**	**0**		
Absolute Net Change	**3.3**	**2.2**	**1.4**	**1.3**		
Gain Analysis						
Expected (Random) Value						
Tree	**13.4**	**4.9**	**5.8**	**0.5**		
Shrub grass	**1.3**	**13.1**	**9.3**	**0.8**		
Bare ground	**1.7**	**8.4**	**36.2**	**1.0**		
Urban	**0.1**	**0.3**	**0.4**	**1.1**		
Difference between Actual and Expected						
Tree	**0.0**	**-0.8**	**-4.4**	**0.5**		
Shrub grass	**0.8**	**0.0**	**2.2**	**0.0**		
Bare ground	**-1.2**	**3.1**	**0.1**	**-0.5**		
Urban	**0.4**	**0.7**	**0.6**	**0.0**		
Difference divided by Expected						
Tree	**0.0**	**-0.2**	**-0.8**	**1.0**		
Shrub grass	**0.6**	**0.0**	**0.2**	**0.0**		
Bare ground	**-0.7**	**0.4**	**0.0**	**-0.5**		
Urban	**8.9**	**2.4**	**1.8**	**0.0**		

Table 5-6 Continued

	2005↓			
2000→	Tree (%)	Shrub grass (%)	Bare ground (%)	Urban (%)
Loss Analysis				
Expected (Random) Value				
Tree	**13.4**	**2.4**	**4.1**	**0.3**
Shrub grass	**3.3**	**13.6**	**10.0**	**0.7**
Bare ground	**4.0**	**7.3**	**36.3**	**0.8**
Urban	**0.4**	**0.8**	**1.3**	**1.1**
Difference between Actual and Expected				
Tree	**0.0**	**1.7**	**-2.7**	**0.7**
Shrub grass	**-1.2**	**-0.5**	**1.5**	**0.1**
Bare ground	**-3.5**	**4.2**	**0.0**	**-0.3**
Urban	**0.1**	**0.2**	**-0.3**	**0.0**
Difference divided by Expected				
Tree	**-0.1**	**0.9**	**-0.6**	**2.5**
Shrub grass	**-0.8**	**0.0**	**-0.4**	**-0.5**
Bare ground	**-1.0**	**-0.5**	**0.1**	**-0.8**
Urban	**1.6**	**2.8**	**1.1**	**1.2**

5.4 The analysis of land cover by category

This section analyses each land cover change spatially in order to examine the distribution of change according to the earlier subdivision of the study area by physiographic region (Figure 1-1). This was conducted to answer the question of how each land cover class changes at various times across the four regions. The regions are: Gamawa-Jakusko plain (14% of the study area), the Fadama (7%), Potiskum plain (55%) and Gudi-Jonga hills (24%)

5.4.1 The tree land cover

The spatial characteristics of the tree land cover between 1986 and 2005 are presented in Table 5-7. The column 'Transition Area' provides the percentage of the transition category of the change in the study area for each time period identified (pale blue, total of all equal to 100). The other columns show the distribution of the 'Transition

Category' according to region (Yellow). For example the 'Tree in 1986 only' meaning the tree category that appeared only in 1986 and did not occur again but changed to another category was only 16% of the total number of pixels that related to tree during the study period. Of the 'Tree in 1986 only' 4% was in the Gamawa-Jakusko plain, 19% in the Fadama, 29% in the Potiskum plain and 48% in the Gudi-Jonga hills. This implies that approximately half the tree that was lost before 2000 happened in the Gudi-Jonga hills. From the table most of the change and the no changes happened in the Gudi-Jonga hills. 57% of the tree transition areas were areas that did not change over the period of the study and over 90% of this was in the Gudi-Jonga hills. Partially persistent trees, that is, 'Tree in 1986 and 2000 only' (10%) and 'Tree 2000 and 2005 only' (5%) occurred mainly in the Fadama and Gudi-Jonga hills. 'Tree in 2000 only' and 'Tree in 2005 only' were conversion of other land cover categories to tree at the two dates, however, the 'Tree in 2000 only' converted to another category before 2005. The 'Tree in 1986 and 2005' accounted for 3% of the transition and demonstrated a kind of resilience of the tree category, meaning tree was lost and recovered. 87% of this happened in the Gudi-Jonga hills.

The graphical representation of the transition of the tree category is presented in Figure 5-2. The changes in the Potiskum plain were limited to the area north of Dawasa and Nangere and in the neighbourhood of the Gudi-Jonga hills. The transitions in the tree category were mostly in the Gudi-Joga hills and the Fadama (Figure 5-2). Several areas were selected to show areas with intensive change (Figure 5-3): areas A and C with intensive transition of the tree category that was lost by 2000 in the Fadama, one in the Potiskum plain (D in Figure 5-3) and one in the Gudi-Jonga hills (E in Figure 5-3). While more tree was loss in the Gudi Jonga hills after 1986 the loss was not concentrated at one location only but more generally spread. The loss of tree after 2000 was also generally spread in the Gudi-jonga hills with some pockets of intensive change (Figure 5-4).

Table 5-7: Distribution of the tree transition according to time and by region

Transition Category	Total Transition Area (%)	Distribution by Region			
		Gamawa-Jakusko plain (%)	Fadama (%)	Potiskum plain (%)	Gudi-Jonga hills (%)
Tree in 1986 only	16	4	19	29	48
Tree in 1986 and 2000 only	10	1	36	12	51
Tree in 1986, 2000 and 2005 only	57		5	4	91
Tree in 1986 and 2005 only	3		10	4	86
Tree in 2000 only	5	6	29	27	38
Tree in 2000 and 2005 only	5		29	27	44
Tree in 2005 only	4		21	20	59

A regional change density (RCD) was introduced in order to show the relative loss or gain of a land cover according to regions. Table 5-7 provides the percentage of each transition category and how each was distributed in the four regions, however it does not indicate how it relates to the size of the region and hence its impact. In order to relate the change to the size of the region the concept of density was applied, which is the element of a transition category in a particular region per size of the region. In order to facilitate comparison between the regions and transition categories, the elements of the transition category by region was transformed to a singular denominator, that is, the study area. Thus a new intermediary table (Table 5-8) was computed by multiplying the percentage of the transition category by each distribution by region value (Table 5-7). Each element of Table 5-8 was then divided by the region's area percentage to compute the density (Table 5-9).

The following interpretations can be made from the RCD for the tree land cover (Table 5-9): There was a very high tree RCD of tree persistence in the Gudi-Jonga hills, about five times higher than any other type of tree transition in any area. This was consistent with the quantity that persisted (Table 5-7). There was a higher RCD in the other transition categories in the Fadama area than anywhere else, suggesting a higher change impact per area in the region. The low RCD of tree in the Gamawa-Jakusko plain was mainly due to the low total quantity of the tree class, but the low RCD in the Potiskum plain was mainly due to its size compared to the other regions.

Table 5-8: Distribution of the tree transition according to region in percentage of the tree transition

Transition Category	Distribution by Region			
	Gamawa-Jakusko plain (%)	Fadama (%)	Potiskum plain (%)	Gudi-Jonga hills (%)
Tree in 1986 only	0.64	3.04	4.64	7.68
Tree in 1986 and 2000 only	0.1	3.6	1.2	5.1
Tree in 1986, 2000 and 2005 only		2.85	2.28	51.87
Tree in 1986 and 2005 only		0.3	0.12	2.58
Tree in 2000 only	0.3	1.45	1.35	1.9
Tree in 2000 and 2005 only		1.45	1.35	2.2
Tree in 2005 only		0.84	0.8	2.36

Table 5-9: The tree regional change density

Transition Category	Distribution by Region			
	Gamawa-Jakusko plain	Fadama	Potiskum plain	Gudi-Jonga hills
Tree in 1986 only	4.6	43.4	8.4	32
Tree in 1986 and 2000 only	0.7	51.4	2.2	21.3
Tree in 1986, 2000 and 2005 only		40.7	4.1	216.1
Tree in 1986 and 2005 only		4.3	0.2	10.8
Tree in 2000 only	2.1	20.7	2.5	7.9
Tree in 2000 and 2005 only		20.7	2.5	9.2
Tree in 2005 only		12	1.5	9.8

Note: this is a ratio of change to size of region

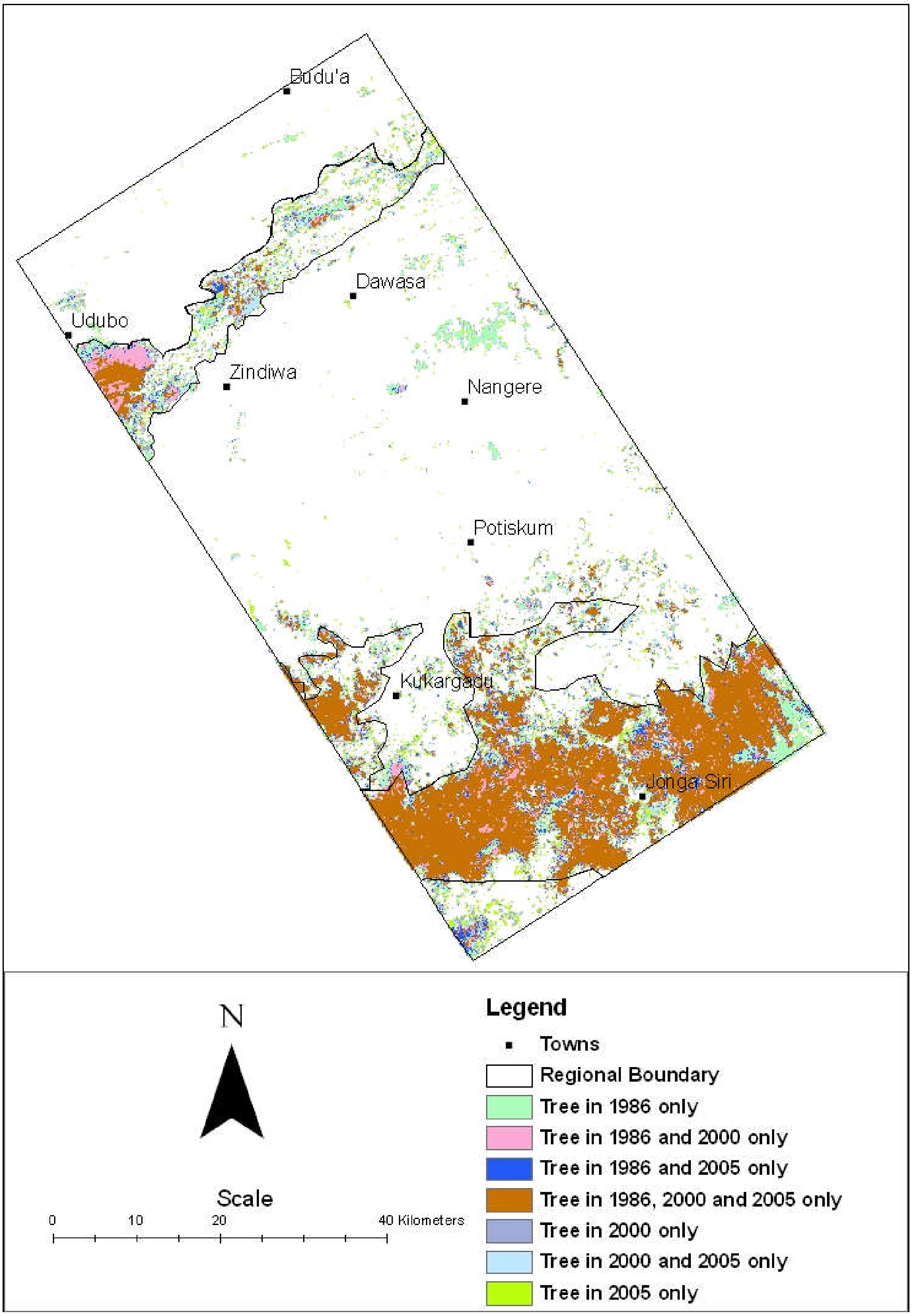


Figure 5-2: The tree transition map 1986 to 2005

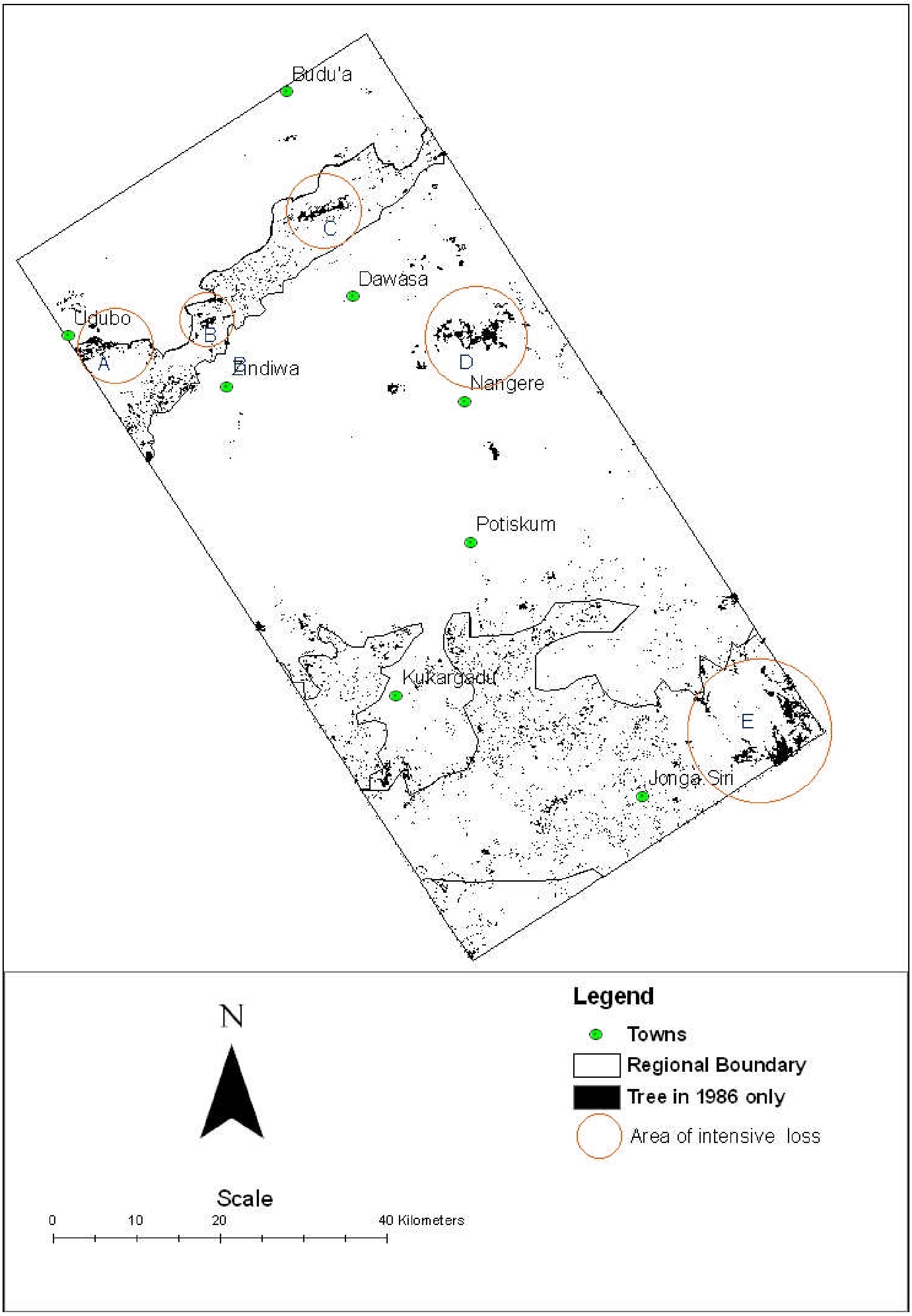


Figure 5-3: Tree distribution in 1986 only

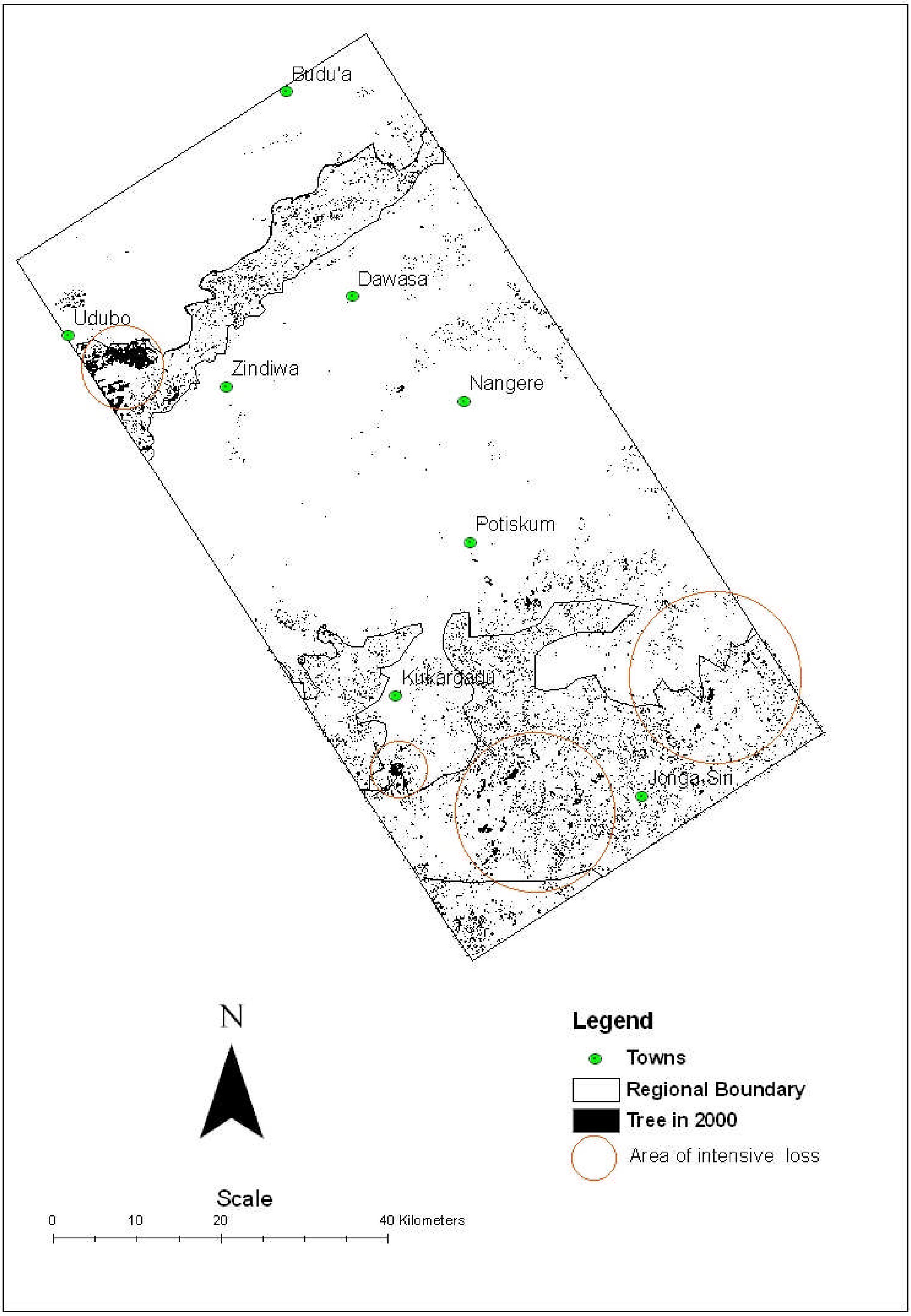


Figure 5-4: Tree distribution in 2000 only

5.4.2 *The shrub grass land cover*

The shrub grass category tended to be the most dynamic land cover with only 17% (Table 5-10) of the shrub grass transition area persisting during the period of the study, unlike the tree (section 5.4.1). Most of the shrub grass that persisted was in the Potiskum plain and the Gudi-Jonga hills. About 30% of the shrub grass in 1986 was lost by 2000, however, there was new growth of 23% by 2000, and 19% by 2005. About 50% to 65% of all categories of transition of the shrub grass category happened in the Potiskum plain. Most of the loss in the shrub grass happened in the Potiskum plain and the Fadama. The RCD in the Fadama was still high as with the tree category (Table 5-9) but its variation from the other classes was less than with the tree category (Tables 5-9 and 5-11). Although most of the changes happened in the Potiskum plain its area makes the RCD slightly smaller.

Figure 5-6 shows the changes in the shrub grass according to the seven categories of change. Unlike the tree persistence from 1986 to 2005 (Figure 5-2) in the Gudi-Jonga hills dominating the transition map, the shrub grass persistence between 1986 and 2005 did not exist (Figure 5-5). The two intensive areas of transition of the shrub grass are further demonstrated in Figures 5-6 and 5-7. The first was the loss of shrub after 1986, with the lowest losses in the Gudi-jonga hills and with intense losses in areas north east of Udubo, north of Dawasa and Budua (Figure 5-6). The second was the state of shrub grass by 2005 indicating a general spread with an area of intensive change to the south of Udubo (Figure 5-7).

Table 5-10: Distribution of the shrub grass category according to transition categories

Transition Category	Transition Area (%)	Distribution by Region			
		Gamawa-Jakusko plain (%)	Fadama (%)	Potiskum plain (%)	Gudi-Jonga hills (%)
Shrub grass in 1986 only	30	34	11	48	7
Shrub grass in 1986 and 2000 only	8	27	8	53	12
Shrub grass in 1986, 2000 and 2005 only	17	3	7	59	31
Shrub grass in 1986 and 2005 only	11	3	11	64	22
Shrub grass in 2000 only	7	16	4	63	17
Shrub grass in 2000 and 2005 only	8	1	9	55	35
Shrub grass in 2005 only	19		12	66	21

Table 5-11: Shrub grass transition regional change density

Transition Category	Distribution by Region			
	Gamawa-Jakusko plain	Fadama	Potiskum plain	Gudi-Jonga hills
Shrub grass in 1986 only	72.9	47.1	26.2	8.8
Shrub grass in 1986 and 2000 only	15.4	9.1	7.7	4
Shrub grass in 1986, 2000 and 2005 only	3.6	17	18.2	22
Shrub grass in 1986 and 2005 only	2.4	17.3	12.8	10.1
Shrub grass in 2000 only	8	4	8	5
Shrub grass in 2000 and 2005 only	0.6	10.3	8	11.7
Shrub grass in 2005 only		32.6	22.8	16.6

Note: this is a ratio of change to size of region

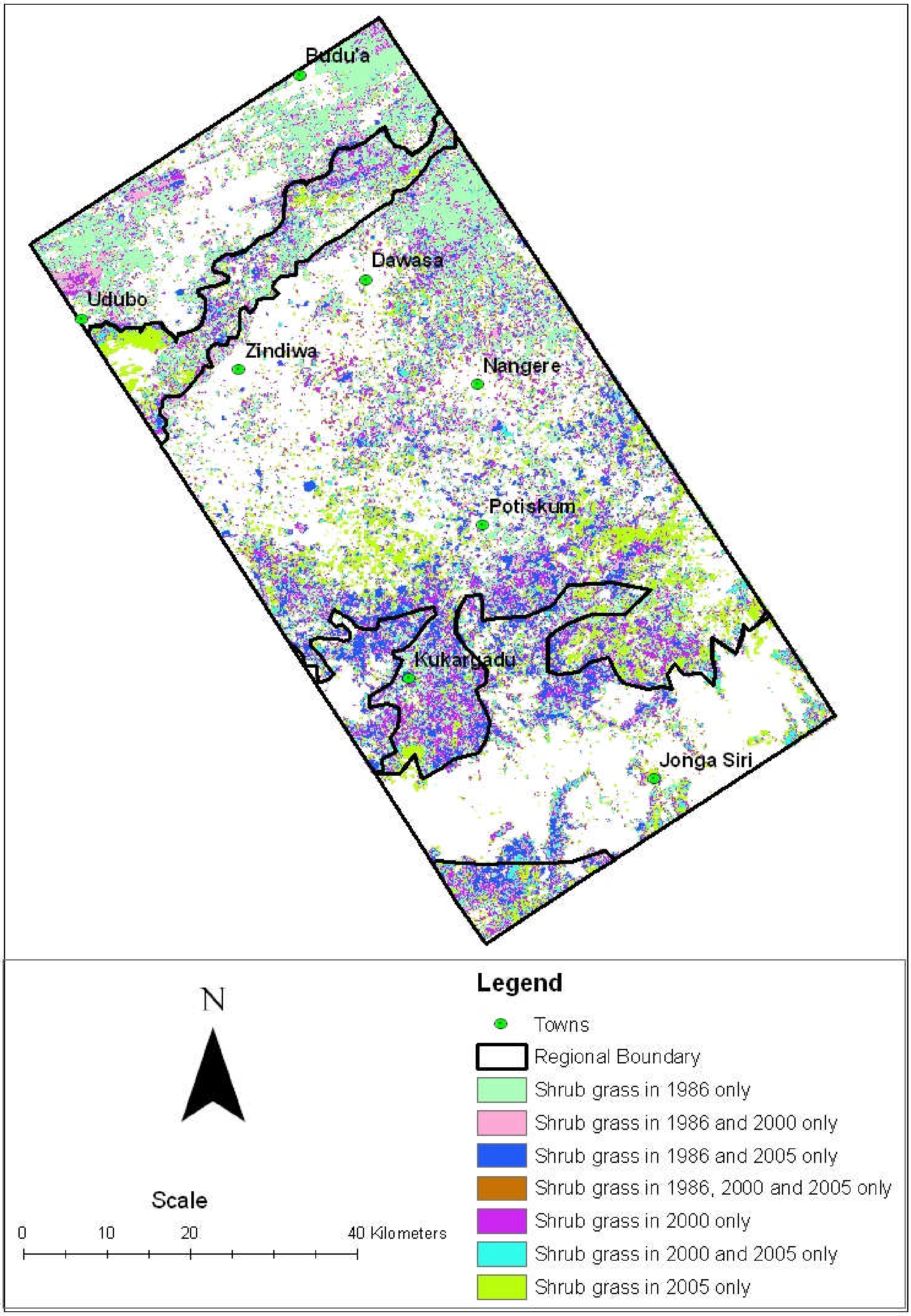


Figure 5-6: Land cover change of shrub grass from 1986 to 2005

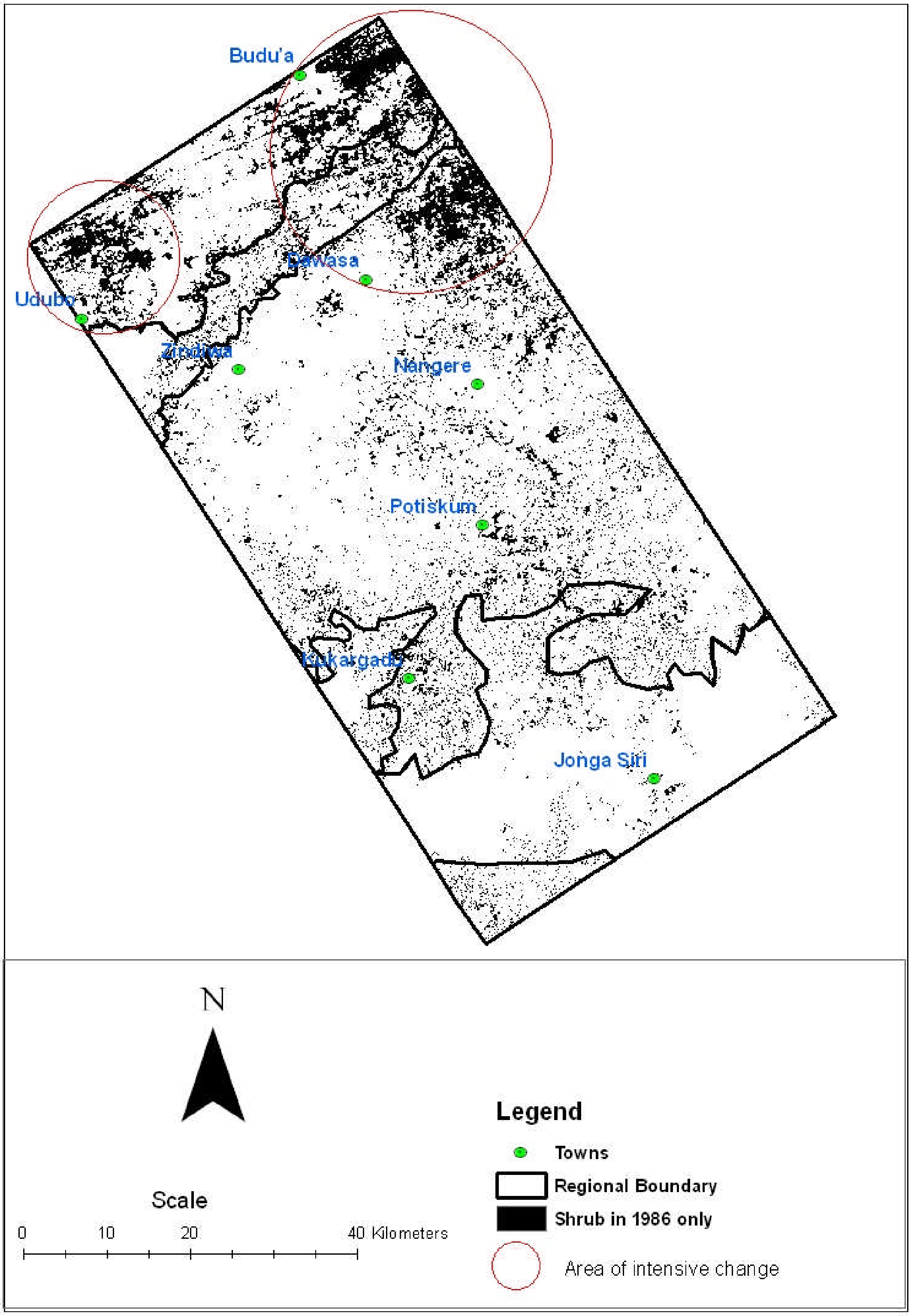


Figure 5-7: Shrub grass extent in 1986 only

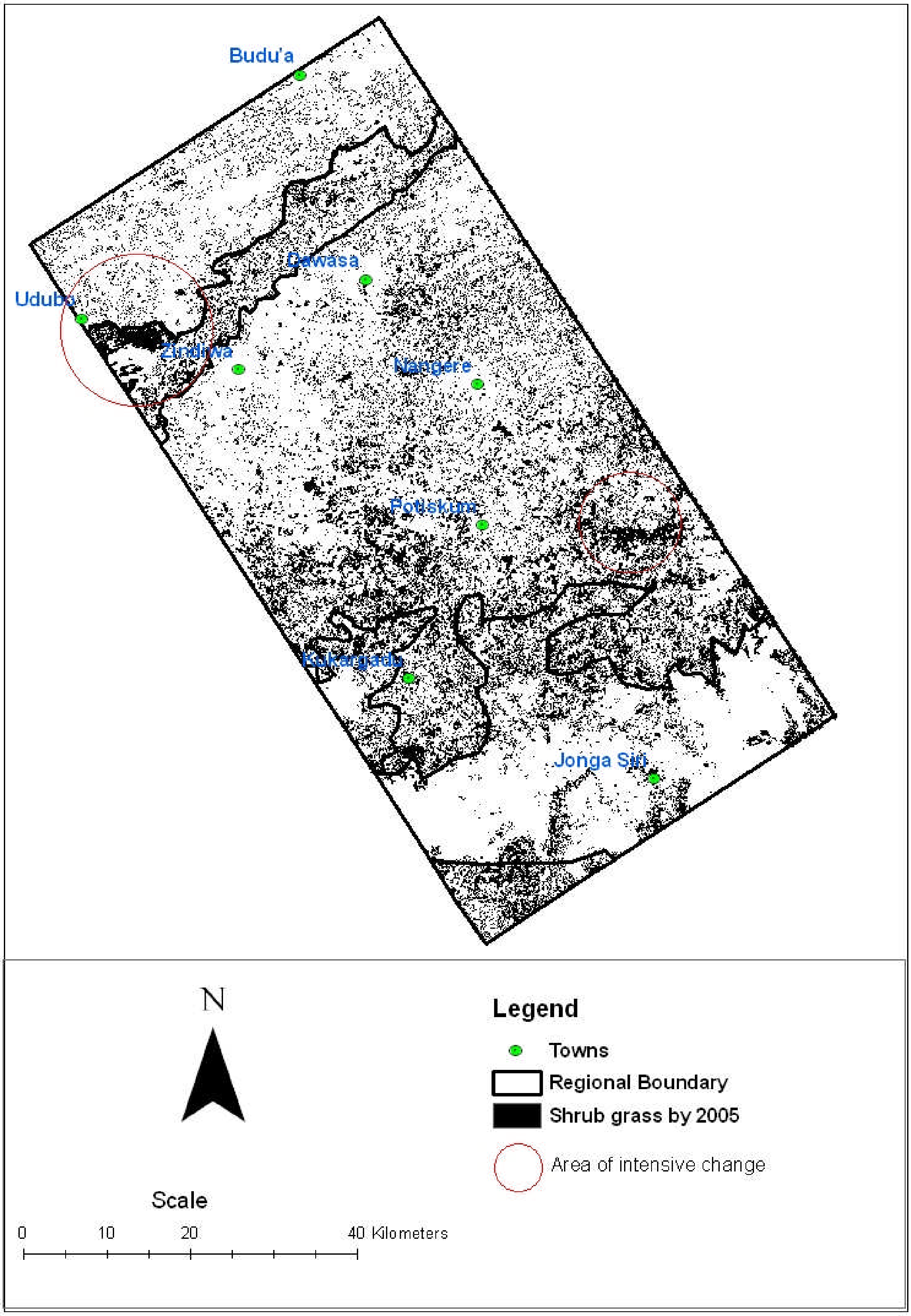


Figure 5-8: Shrub grass in 2005 only

5.4.3 Bare ground

The changes in bare ground are represented in Table 5-12 and Figure 5-8. Over 70%, of the transition occurred in the Potiskum plain except bare ground only in 2005 and new bare ground by 2000 that continued to 2005 (Table 5-12). Over 50% of the bare ground was unchanged during the period of the study, another 17% remain unchanged from 2000 to 2005. While there was a loss of 9% after 2000 there was a gain of 8% in 2005.

The appearance of bare ground by 2000 (Figure 5-9), an indication of either degradation of tree or shrub grass or the expansion of agricultural land, occurred intensely to the north of Udubo and Nangere and south east of Budua. This occurrence of new bare ground happened again by 2005 although with lower intensity (Figure 5-10).

Table 5-12: Distribution of bare ground according to transition categories

Transition Category	Transition Area (%)	Distribution by Region			
		Gamawa-Jakusko plain (%)	Fadama (%)	Potiskum plain (%)	Gudi-Jonga hills (%)
Bare ground in 1986 only	5	1	3	73	23
Bare ground in 1986 and 2000 only	9			89	11
Bare ground in 1986, 2000 and 2005 only	51	21		78	1
Bare ground in 1986 and 2005 only	4	20	2	76	1
Bare ground in 2000 only	5	4	1	77	18
Bare ground in 2000 and 2005 only	17	4	4	55	2
Bare ground in 2005 only	8	33	18	44	4

Table 5-13: Bare ground transition regional change density

Transition Category	Distribution by Region			
	Gamawa-Jakusko plain	Fadama	Potiskum plain	Gudi-Jonga hills
Bare ground in 1986 only	0.4	2.1	6.6	4.8
Bare ground in 1986 and 2000 only	0.0	0.0	14.6	4.1
Bare ground in 1986, 2000 and 2005 only	76.5	0.0	72.3	2.1
Bare ground in 1986 and 2005 only	5.7	1.1	5.5	0.2
Bare ground in 2000 only	1.4	0.7	7.0	3.8
Bare ground in 2000 and 2005 only	4.9	9.7	17.0	1.4
Bare ground in 2005 only	18.9	20.6	6.4	1.3

Note: this is a ratio of change to size of region

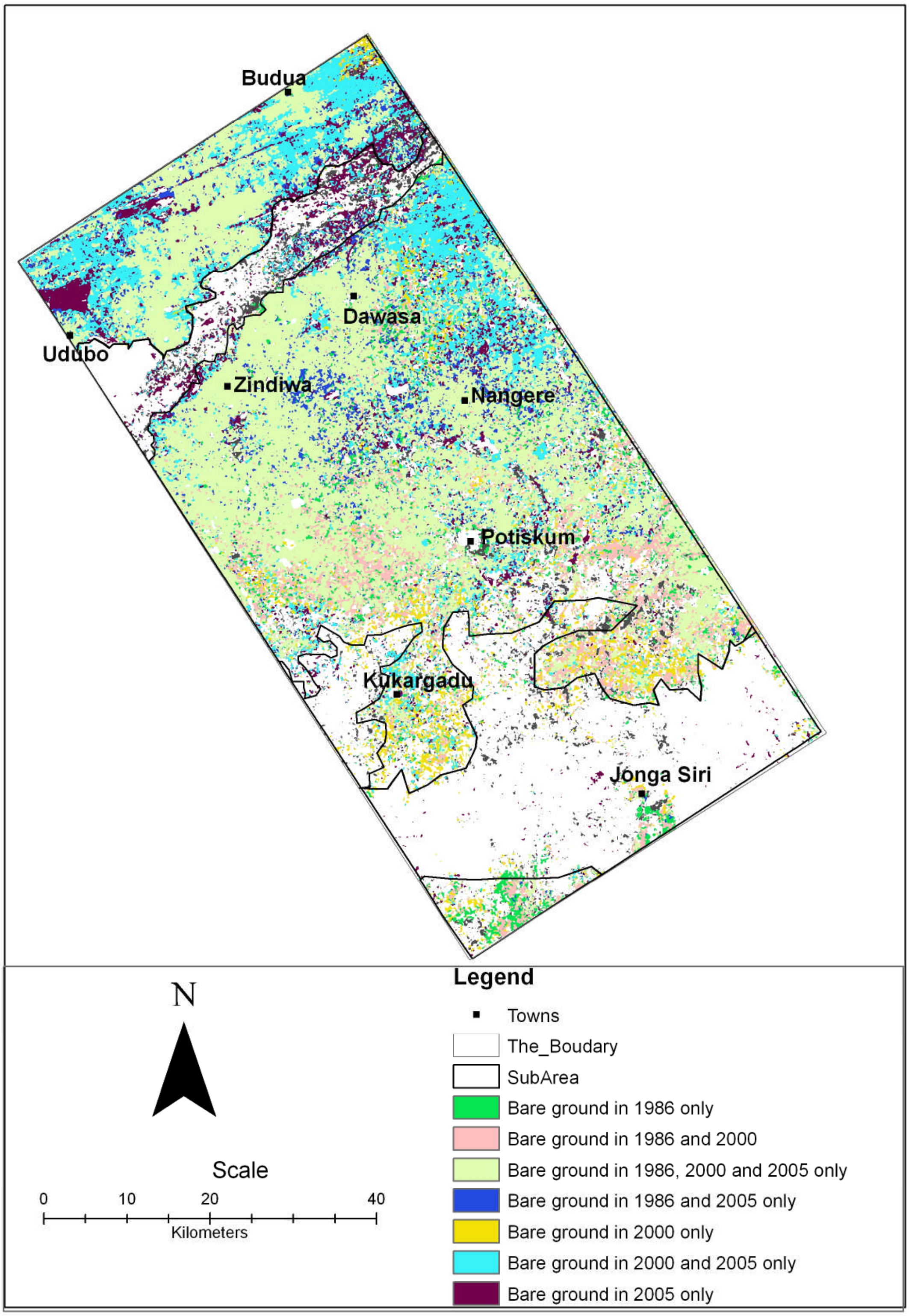


Figure 5-8: Land cover change in bare ground 1986 to 2005.

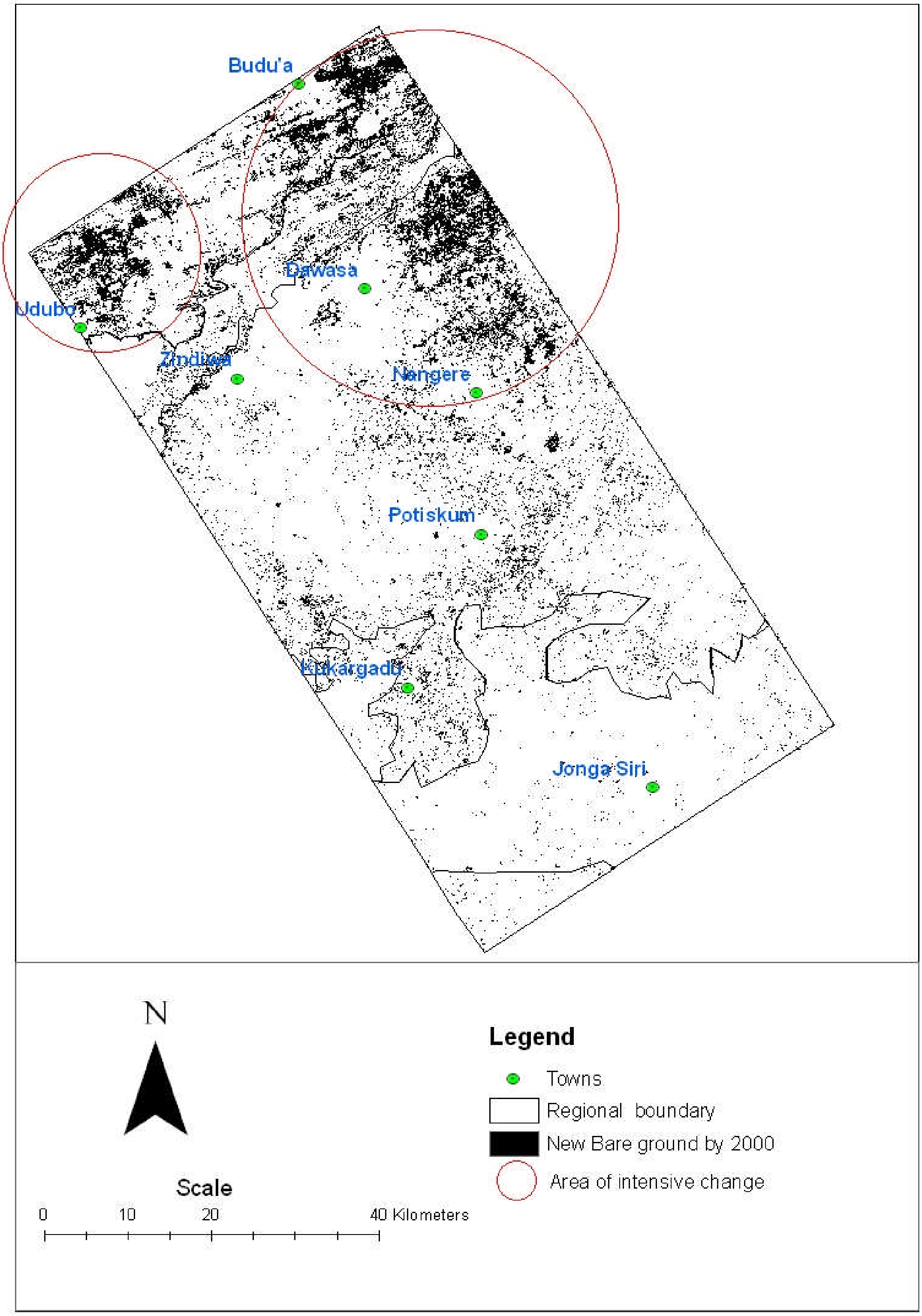


Figure 5-9: New bare ground in the year 2000

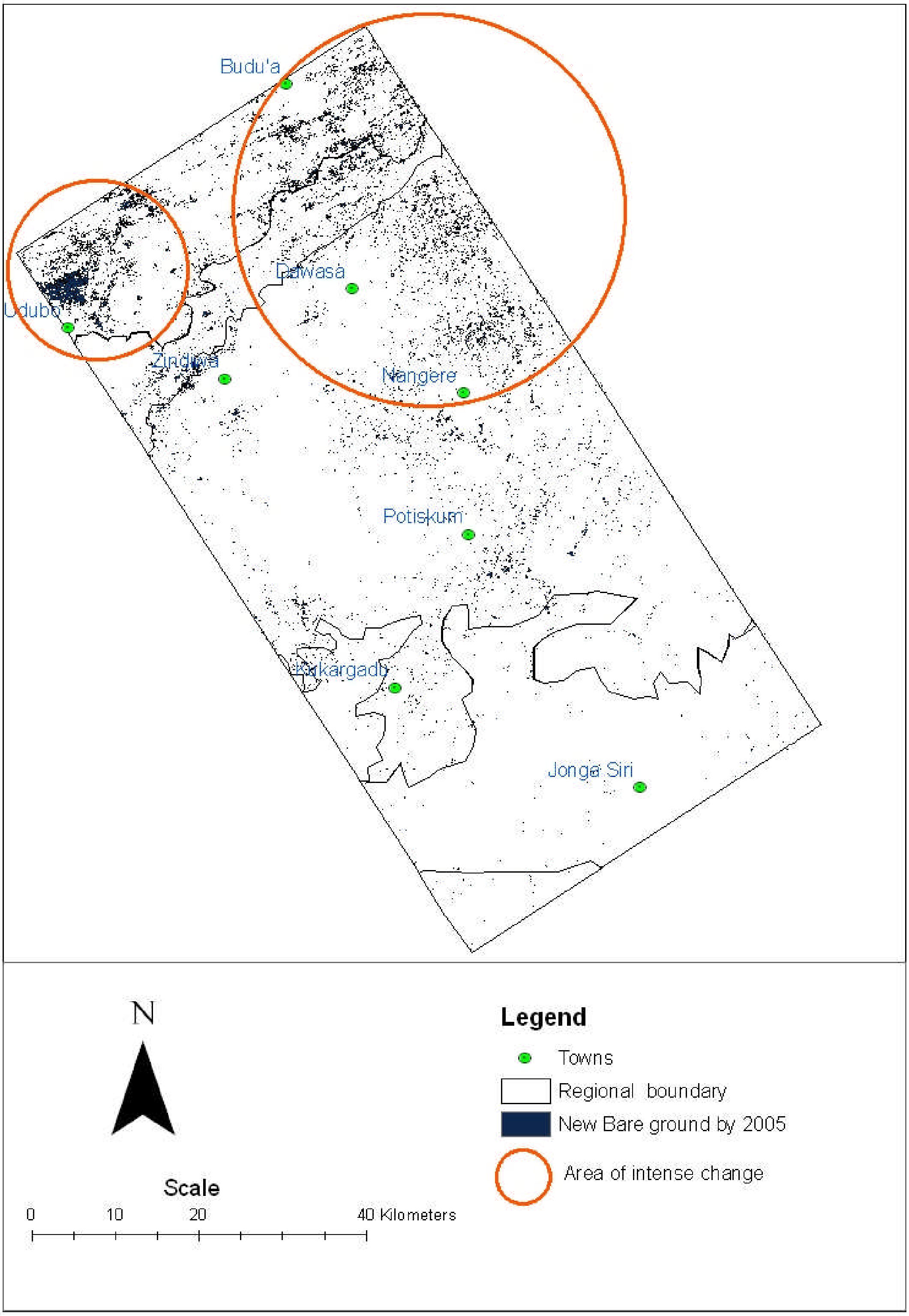


Figure 5-10: New bare ground in the year 2005

5.4.4 The urban land changes

A transition map of the urban area indicated a large area of urban pixels in the Fadama and the south of Potiskum, and also the poor representation of the urban class at the locations of towns and villages are highlighted in Figure 5-11. Only Potiskum town was better classified. This could be because the source of the urban land cover signature was drawn from there and because of the size of the area (Figure 5-11). The other towns and villages were hardly represented either due to their smallness or the material and style of building that does not distinguish itself from the bare ground or the tree or shrub grass categories in their neighbourhood. Thus the transition category matrix such as Table 5-12 produced an erroneous analysis of the urban class. In order to reduce the effect of the distortions due to the misclassification of the category the analysis was focused on the area about the Potiskum town only (Figure 5-12 and Table 5-14).

Within the subset of the study area limited to the neighbourhood of Potiskum Figure 5-13, most of the change occurred in the eastern part of the town with 41% of the transition area increasing between 1986 and 2000 and 26% between 2000 and 2005 (Table 5-14).

Table 5-14: Potiskum area according transition categories

Transition Category	Transition Area (%)
Urban in 1986 only	**1**
Urban in 1986 and 2000 only	**1**
Urban in 1986, 2000 and 2005 only	**29**
Urban in 1986 and 2005 only	**2**
Urban in 2000 only	**13**
Urban in 2000 and 2005 only	**28**
Urban in 2005 only	**26**

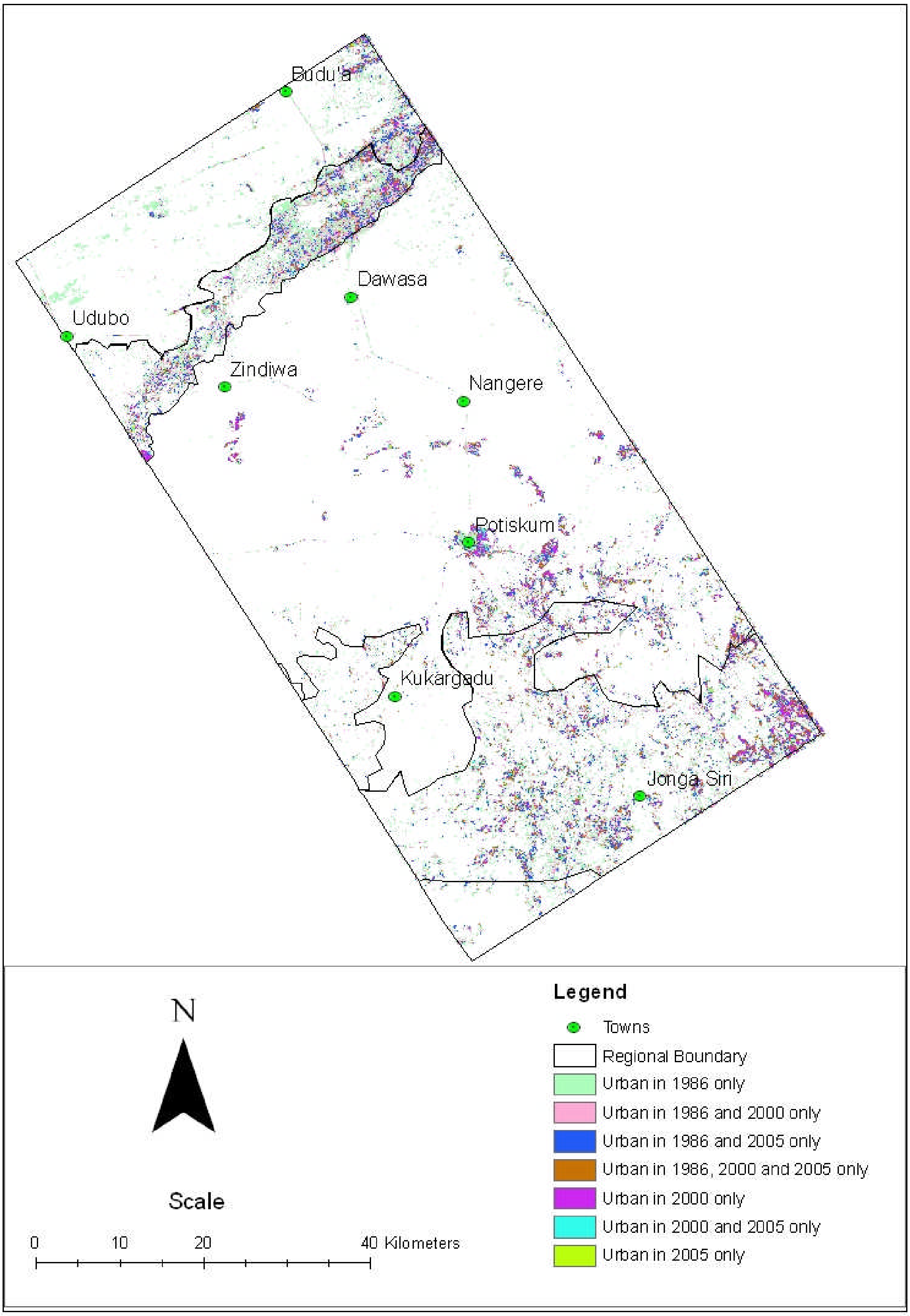


Figure 5-11: Urban land cover change in the study area

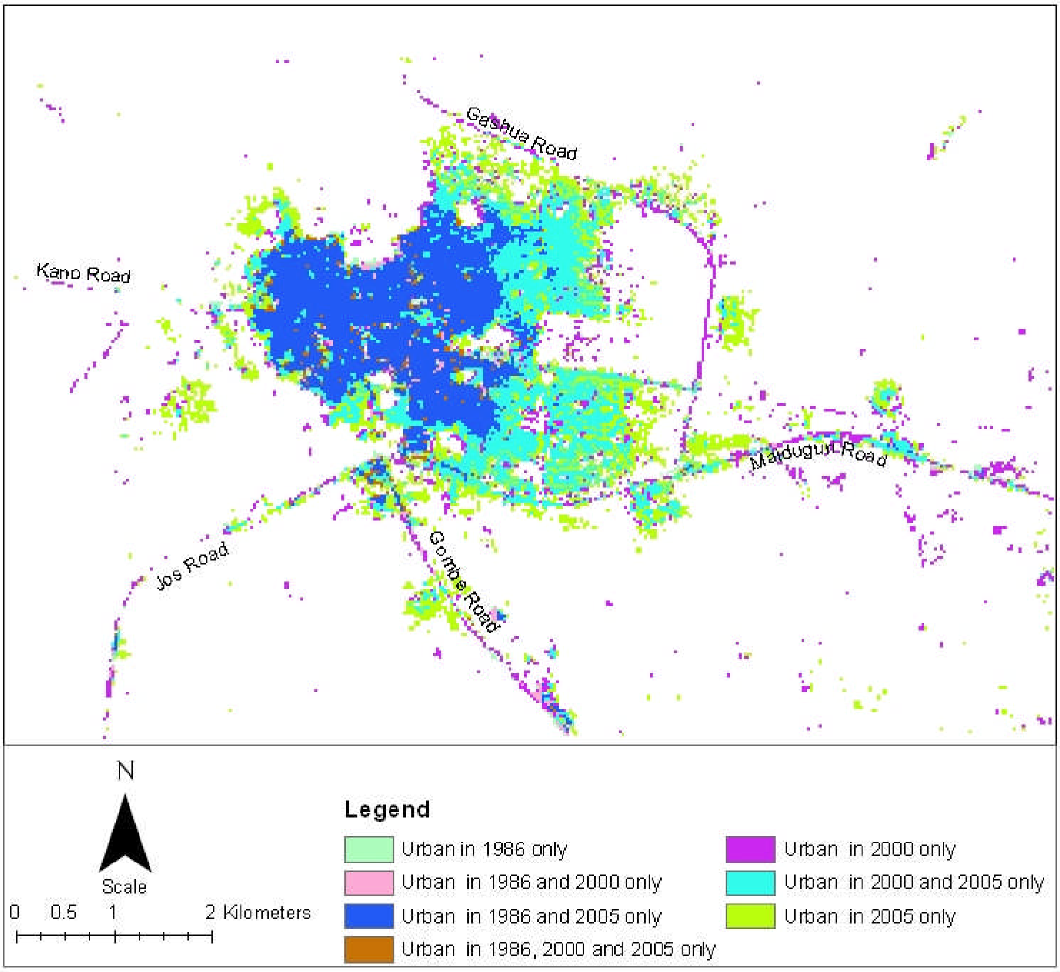


Figure 5-12: Urban land cover change around the Potiskum area

5.4.5 Water

The quantity of water in 1986 was less than 0.1% and 0.2% in 2000 and zero in 2005. There was no persistence of water. This showed that the very few incidences of water were in different locations. In addition the quantity of water was likely to vary with time of the year. Therefore quantifying the changes in surface water from this data would not be correct over the period of the study. It would however be correct to say that there were traces of water in the 1986 and 2000 images. Therefore this analysis was conducted without the water category.

5.4.6 Comparison of tree, shrub grass and bare ground

Only tree, shrub grass and bare ground were analysed in relation to the complete area. Both the tree and the bare ground categories showed high persistence compared to the shrub grass (1986 to 2000, Figure 5-13). There were increases in both the shrub grass and the bare ground in the period 2000 to 2005. The growth of shrub grass indicated a slight shift to shrub dominated land cover toward the southern part of the Potiskum plain matching with the persistence in the tree category in the Gudi-Jonga hills (section 7.3.2).

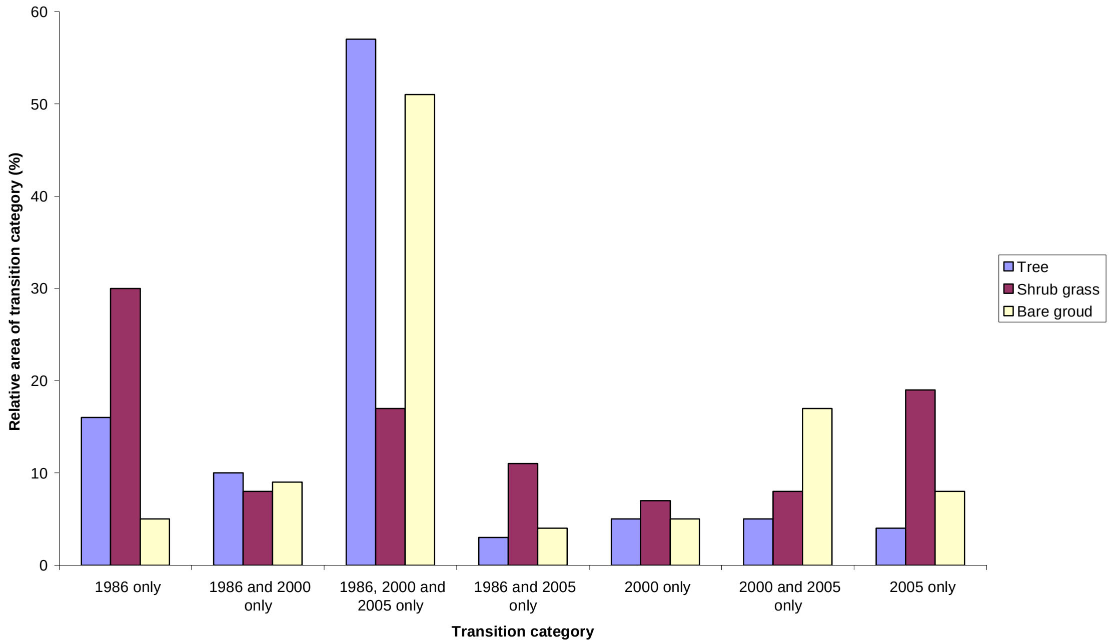


Figure 5-14: Comparison of transition categories of tree, shrub grass and bare ground in the study area

5.5 Land cover change as perceived by people in the study area

A group interview (3 to 8 older men 50 years and above) was conducted across the study at 40 locations (Figure 5-14) with the objective of determining how people in the study area felt about the environmental changes going on around them. The interview was unstructured and was a simple question on what they thought existed in terms of land cover in their areas some 30 years ago, whether there was forest or not, whether there were changes over the time and what they think caused the changes and what they think are the consequences? Further questions on the consequences included the migration and immigration of people, conflict with nomads and any other related issues they felt were important.

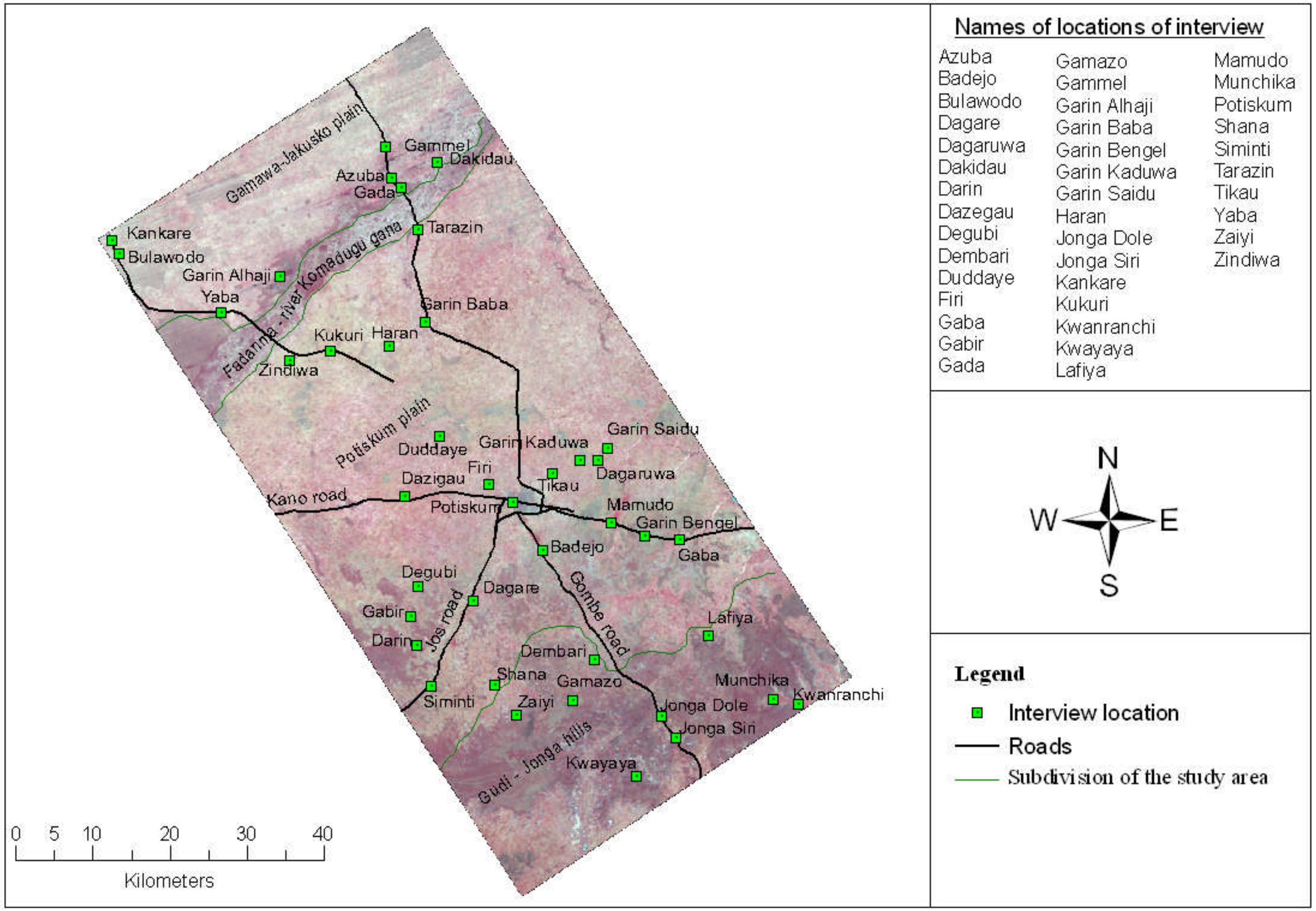


Figure 5-14: Locations of interviews

In all location there was the perception that their surroundings had changed in the last 30 years. The changes related to the loss of wilderness: natural forestry such as woodland and the increase in farmland. This relates to the net loss of tree of 1.5% between 1986 and 2000 and 3% between 2000 and 2005 (Table 5-2). It also relates to the increase in bare ground of 6% between 1986 and 2000 and 1% between 2000 and 2005 (Table 5-2). They felt the increase in family size had led to the need for additional farm land which had affected the extent of the woodland

Gammel in the north eastern corner of the study area in the Gamawa-Jakusko plain was the only location where the loss of the wilderness was associated with an increase in sand deposition providing some supporting evidence for the process of desertification. The perception of the changes in the Fadama was derived from the settlements in the immediate neighbourhood of the Fadama because no settlements exist within the Fadama itself. The people in Gada, Dakidau, Azuba and Tarazin felt that the campaign to eradicate tse-tse flies and construction of the Gashuwa to Potiskum road that occurred about 40 years ago began the degradation of the woodland in the Fadama. Generally the people living in the neighbourhood of the Fadama witnessed the opening of new farmland in the Fadama by people coming from bigger towns like Potiskum, and a lot of people coming to rent land for dry season farming, the situation often leading to conflict among the farmers and the cattle grazers over access to water. Yaba, Gada and Dakidau experience annual immigration of fishermen and dry season farming with the rainy and dry seasons, respectively. The respondents felt that there were weaknesses in the enforcement of the laws that controls the cutting of trees although there were government officials on the ground to restrict tree cutting.

These high demands could be related to the intensity of change (Table 5-9) seen in the Fadama. Thus the change assessment indicated the increasing use of land for grazing and farming is having impact on the Fadama.

In the north of Potiskum and Gamawa-Jakusko plains the people complained of degradation of land as it related to farm yield. The people around Gammel in the Gamawa- Jakusko felt the deposition of sand and drought (or shorter rainy seasons) affected their yield, the people in the northern part of Potiskum plain felt the land was losing its nutrient value. This condition had caused some people to temporarily migrate during the rainy season to areas further south such as Gombe and for some people to abandon farming in order to pursue other, non farming ventures in Potiskum town. In these areas, many villages had to import their wood (fuel) from the southern part of the study area, this meant a great change to them because they were getting their supply of wood from their backyards.

The areas in the neighbourhood of Potiskum such as Firi and Tikau felt that the changes in wilderness had occurred much earlier than the 30 years ago. The changes seen in this area are rather due to the expansion of the town than of the tree land cover. The expansion of the Potiskum town in the east could partly be explained by the migration of people from northern areas coming to the town along the major road.

The implications of the changes are: loss of plant and animal species, loss of yield, temporary migration and conflicts over farmlands and water resources. The people could count tree species locally known as madobia, matsagi, bauche, dakwara, iriya, and animals such as wild pig, hyena, and gazelle that no longer exist. They attributed loss of forest and thick bushes to agricultural expansion. They recalled how it was difficult to get between villages nearby, that they had to cut through thick bushes and were afraid of wild animals, but now they could even see some of the villages from their own village.

Further work is required to link the land cover measurements of the research and the precise measurement of people’s perception and land use. The results point to fact that there are changes going on with implications that include loss of some species, loss of resources, and conflict over resources that require scientific management.

5.6 The transition error matrix

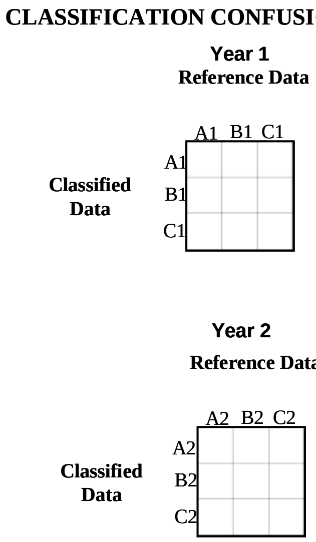
The main sources of error identified by change detection analysis using a post classification method (as in this research) were image registration (as discussed earlier section 2.4.1), the land cover classification definitions, acquisition of data and data processing and analysis processes (Congalton and Green, 1999; van Oort, 2005; Coppin et al, 2004). This change detection process has the tendency of overestimating the change (van Oort, 2005). Hence a method was needed that categorised the change beyond the simple change/no change matrix (van Oort, 2007). One such tool of analysis is the transition error matrix (Bing et al 1999; Congalton and Green, 1999; van Oort, 2007)

If one is interested in improving the summed area of each land cover then the direct method (Bird et al., 2000, explained in section 5.7.1) will be sufficient, since it redistributes the errors in proportion to the land cover and then produces an estimate of the land cover for a particular time.

The transition error matrix compares two confusion matrices from two dates, for example, Year 1 and 2 in Figure 5-15. This means the method compares the classified and reference data of a particular year to the classified and reference data of the same location in another year. The matrix produced becomes a valuable tool of analysis similar to the confusion matrix (Congalton and Green, 1999). It produces the normal 2x2 change\no change matrix and the transition error.

The transition error matrix represents the possible types of change\no change and their corresponding errors in six categories (Binging et al., 1999) and these can be described with the aid of Figure 5-15 using some of their terminologies such as: 'true no change' is represented by the diagonal entries: cells containing the value 1 are pixels that have not changed between the two years and are correctly classified therefore no error is present; 'true change' is represented by the value 2 and are the pixels that are correctly classified but have changed, thus no error is present; 'true no change' is represented by the value 3 which are the pixels that have not changed but are incorrectly classified, hence have classification error; 'true change' is also represented by the value 4 and are pixels that are incorrectly classified although both the reference and the classified data have changed; the value 5 represents 'true change' because the reference data has changed but the classification was incorrect, this is thus termed a false negative; and the value 6 represents 'true no change', however, there was change in the classification, termed false positive.

An expression of accuracy can be deduced in two ways: one relates to detection of change, that is, change detection accuracy, it is the sum of the unchanged values over the total sampled (Figure 5-16a); the other relates to the correct transition termed transition accuracy, this is the sum of no error values over the total sampled (Figure 5-16b) (Macleod and Congalton, 1998; van Oort, 2007).



TRANSITION ERROR MATRIX

Reference Data (columns); Classified Data (rows)

	A1A2	B2B2	C1C2	A1B2	A1C2	B1A2	B1C2	C1A2	C1B2
A1A2	1	3	3	5	5	5	5	**5**	**5**
B1B2	3	1	3	5	5	5	5	5	5
C1C2	3	3	1	5	5	5	5	5	5
A1B2	6	6	6	2	4	4	4	4	4
A1C2	6	6	6	4	2	4	4	4	4
B1A2	6	6	6	4	4	2	4	4	4
B1C2	6	6	6	4	4	4	2	4	4
C1A2	6	6	6	4	4	4	4	2	4
C1B2	6	6	6	4	4	4	4	4	2

Figure 5-15: Transition error matrix formed from the confusion matrices on the left and rearranged to show no change and the change (Adapted from Binging et al., 1999)

a

		Reference	
		No Change	**Change**
Classified	**No Change**	**∑ (1 and 3)**	**∑ (5)**
	Change	**∑ (6)**	**∑ (2 and 4)**
Change detection accuracy =		**∑ (1 and 3)/ ∑ (1, 2, 3…6)**	

b

		Reference			
		Change		**No Change**	
		Correct	**Incorrect**	**Correct**	**Incorrect**
Classified	**No Change**	**∑ (1)**	**∑ (3)**	**∑ (5)**	
	Change	**∑ (6)**		**∑ (2)**	**∑ (4)**
Transition detection accuracy =		**∑ (1 and 2)/ ∑ (1, 2, 3…6)**			

Figure 5-16: Condensed transition matrix: a). Change detection accuracy; b). Transition detection accuracy (after van Oort, 2007; Macleod and Congalton, 1998).

Transition error matrices were constructed for 1986 to 2000 (Table 5-15) and 2000 to 2005 (Table 5-18) as earlier described in section 5.2.2 and Figure 5-2. From the matrices the change accuracy was computed to be 64% and 59% and the transition accuracies to be 51% and 45% for 1986 to 2000 and 2000 to 2005 periods, respectively.

The transition error matrices were then normalised in order to express their elements as a percentage of the total sample points, this provided for comparison in percentage of the total sample. This was achieved by dividing each of the elements by the total and multiplying it by 100. Thus the table gives the proportion of each pixel type according to the classification in the two years and their reference class. For example 9% of the pixels sampled in the area were correctly classified as tree in 1986 and remained tree 2000.

Coloured cells were used in Table 5-16 to illustrate the analysis of the transition error matrix in accordance with section 5.2.2. The diagonal elements (modified to remove the zero values) with yellow background indicated no error in the transition and no change, for example, 20% of the sample was bare ground that did not change and was correctly classified. The turquoise background indicates the elements that were correctly classified in the two times but changed category, for example, about 7% of the sample was identified as a correct conversion of shrub grass to bare ground. The light green background are the pixels that at both times the classifications were wrong in the same way, for example 2% were pixels that were shrub grass but classified as bare ground at the two dates. The pink background is false positive error (Binging et al., 1999) and refers to the pixels whose reference had not changed but at least one of the classifications was wrong, for example, 3% of the sample are errors due to the wrong classification of shrub grass as bare ground in the second year although it was correctly classified in the first year. The lavender colour refers to the pixels whose reference has changed but at least one of the classified datasets was wrong, for example 0.8% of the sample had their reference changed from bare ground to shrub grass but their classified changed from shrub grass to bare ground. And finally, the rose background are pixels whose references have changed and although at least one of their classifications was wrong they were classified as the same at the two dates, for example 4.5% were bare ground that became shrub grass however they were both classified as bare ground.

The individual errors greater than 1% were all related to shrub grass in the transition between 1986 and 2000 accounting for 29% of the sample. This was about 67% of the total error (deduced from Table 5-17). Relating the error to the size of the land, that is,

Table 5-5 compared to Table 5-17, showed a high coefficient of correlation with an r-square value of 0.76 (Figure 5-17).

In the 2000 to 2005 transition (Table 5-19) the transition errors greater than 1% of the sample were also related to the shrub grass. The errors were similar with the change of bare ground to shrub grass in which both were classified as bare ground accounting for approximately 7%. Here the shrub grass related error accounted for 29% of the sample and the correlation coefficient was also high at 0.85 (Figure 5-17).

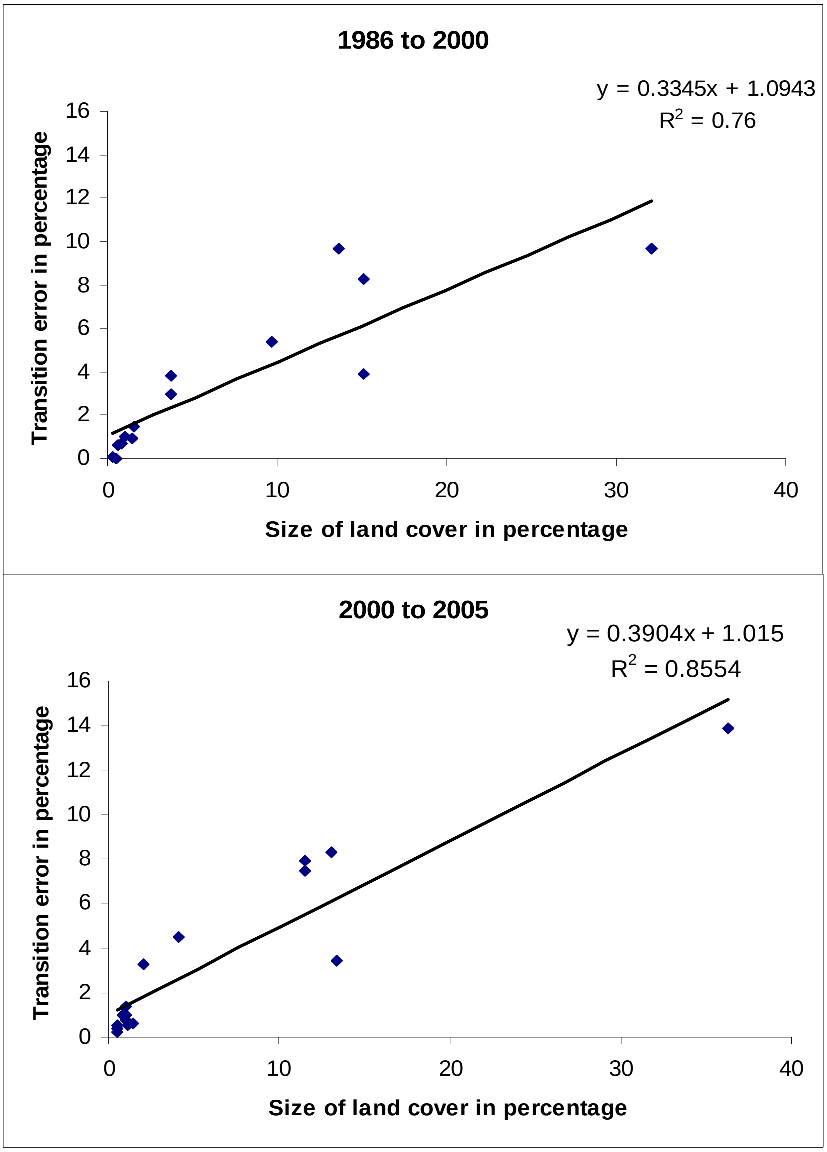


Figure 5-17: The relationship between transition error and the proportionate size of land cover

Table 5-15: The 1986-2000 transition error matrix

	Reference:1986	1	2	3	4	1	1	2	2	2	3	3	3	3	4	4	5	5	5	5
	Reference:2000	**1**	**2**	**3**	**4**	**2**	**3**	**1**	**3**	**4**	**1**	**2**	**4**	**5**	**1**	**3**	**1**	**2**	**3**	**4**
Classified:1986	**Classified:2000**																			
1	1	299	22	1		41	10	47	2		7	3								
2	2	13	206	73		24	14	35	78	2	7	82			3	3				3
3	3	0	69	671		1	1		105		2	153	2							
4	4			1	57							1								
5	5																		5	
1	2	46	23	1	1	62	17	22	8		2	8						2		
1	3	6	6			7	7		9			3						1		
1	4	3	6	4	2	3	5		9		1	1								
1	5	2									1						1			
2	1	10	33	7		10	3	16	5		13	22								
2	3		96	139		8	10	1	235	1		28	1							
2	4		4	32	1	1	1	2	10	1		1								
2	5					1						1						1		
3	1		10	2				2	1		3	7		1						
3	2	1	72	84			1	2	18		8	189	1							
3	4		3	12					1			4								
4	1				1															
4	2								2											
4	3			1																
5	1							1									2			
	Transition Accuracy	51																		
	Change Accuracy	64																		

Note: 1= Tree, 2= Shrub grass, 3= Bare ground, 4= Urban, 5= Water

Table 5-16: The 1986-2000 normalised transition error matrix

	Reference:1986	1	2	3	4	1	1	2	2	2	3	3	3	4	4	5	5	5
	Reference:2000	**1**	**2**	**3**	**4**	**2**	**3**	**1**	**3**	**4**	**1**	**2**	**4**	**1**	**3**	**1**	**2**	**3**
Classified:1986	**Classified:2000**																	
1	1	8.7	0.7			1.2	0.3	1.4	0.1		0.2	0.1						
2	2	0.4	6	2.1		0.7	0.4	1	2.3	0.1	0.2	2.4		0.1	0.1			
3	3		2	19.6					3.1		0.1	4.5	0.1					
4	4				1.7													
5	5																	0.1
1	2	1.3	0.7			1.8	0.5	0.6	0.2		0.1	0.2					0.1	
1	3	0.2	0.2			0.2	0.2		0.3			0.1						
1	4	0.1	0.2	0.1	0.1	0.1	0.1		0.3									
1	5	0.1																
2	1	0.3	1	0.2		0.3	0.1	0.5	0.1		0.4	0.6						
2	3		2.8	4.1		0.2	0.3		6.8			0.8						
2	4		0.1	0.9				0.1	0.3									
3	1		0.3	0.1				0.1			0.1	0.2						
3	2		2.1	2.4				0.1	0.5		0.2	5.5						
3	4		0.1	0.3								0.1						
4	2								0.1									
5	1															0.1		
	Transition Accuracy	51																
	Change Accuracy	64																

Note: 1= Tree, 2= Shrub grass, 3= Bare ground, 4= Urban, 5= Water. Yellow = Pixels where the reference and classified data had not changed and are correct; light green = pixels whose reference and classified data did not change but are incorrect; rose = pixels whose reference data did change but the classified data did not; lavender = pixels that had reference and classified data changed but were incorrect; turquoise = pixels that had reference and classified data changed and are correct; purple = pixels where reference data was unchanged but the classified data changed.

Table 5-17: Summary of the 1986 – 2000 transition error matrix

			Error in Transition		Percentage of the sample						
1986	2000	Correct Transition	No Change	Change	Correct No Change	Correct Change	Error No Change	Classification Error	False Positive	False Negative	Total
Tree	Tree	69.2	5.32	25.5	8.7		0.7			3.2	12.6
Shrub grass	Shrub grass	38.1	15.9	45.9	6.0		2.5			7.2	15.7
Bare ground	Bare ground	66.8	6.87	26.3	19.6		2.0			7.7	29.3
Urban	Urban	96.6	1.69	1.69	1.7					0.0	1.7
Water	Water									0.1	0.1
Tree	Shrub grass	32.3		67.7		1.8		1.7	2.0		5.6
Tree	Bare ground	15.4		82.1		0.2		0.6	0.4		1.1
Tree	Urban							0.5	0.5		1.0
Tree	Water								0.1		0.1
Shrub grass	Tree	13.4		86.6		0.5		1.5	1.5		3.5
Shrub grass	Bare ground	45.3		54.7		6.8		1.3	7.1		15.1
Shrub grass	Urban	1.9		98.1		0.0		0.4	1.0		1.4
Bare ground	Tree	11.5		88.5		0.1		0.3	0.4		0.8
Bare ground	Shrub grass	50.3		49.7		5.5		0.8	4.5		11.0
Bare ground	Urban							0.1	0.4		0.6
Urban	Shrub grass							0.1			0.1
Water	Tree	66.7		33.3		0.1			0.0		0.1
Total					36	15	5.2	7.3	17.9	18.2	96.6

Table 5-18: The 2000-2005 transition error matrix

	Reference:2000	1	2	3	4	1	1	1	2	2	2	3	3	3	5
	Reference:2005	**1**	**2**	**3**	**4**	**2**	**3**	**4**	**1**	**3**	**4**	**1**	**2**	**4**	**3**
Classified:2000	**Classified:2005**														
1	1	232	23	2		32	11		36	2		9	2		
2	2	29	234	46	1	7	12	2	44	66		19	62		
3	3		93	642	3				1	14		4	233	5	
4	4	1	2	7	59					2			5		
1	2	67	36	3		31	7		19	14		3	7		
1	3	2	5			1	3			12					1
1	4	4	2	3	1	8	3		1	1			3		
2	1	66	25	1		3			34	3		11	5		
2	3	3	14	14	2		9	1	2	137	1	3	42		
2	4	5	12	3	1	2			4	4		3			
3	1	2		1			1		4	5		5	4		
3	2	2	86	117		1	3		6	32		11	156		
3	4		2	3						5		2	1		
4	1	1	1	1		2						1	1		
4	2	1	13	14	2					1			18		
4	3		2	26		1	1			3			2		
5	1	2	1			1							3		
5	3		1	1						1			1		
5	4					1									
Transition Accuracy		45													
Change Accuracy		59													

Note: 1= Tree, 2= Shrub grass, 3= Bare ground, 4= Urban, 5= Water

Table 5-19: The 2000-2005 normalised transition error matrix

	Reference:2000	1	2	3	4	1	1	1	2	2	2	3	3	3
	Reference:2005	1	2	3	4	2	3	4	1	3	4	1	2	4
Classified:2000	**Classified:2005**													
1	1	6.7	0.7	0.1		0.9	0.3		1	0.1		0.3	0.1	
2	2	0.8	6.8	1.3		0.2	0.3	0.1	1.3	1.9		0.6	1.8	
3	3		2.7	18.6	0.1					4.1		0.1	6.8	0.1
4	4		0.1	0.2	1.7					0.1			0.1	
1	2	1.9	1	0.1		0.9	0.2		0.6	0.4		0.1	0.2	
1	3	0.1	0.1				0.1			0.3				
1	4	0.1	0.1	0.1		0.2	0.1						0.1	
2	1	1.9	0.7			0.1			1	0.1		0.3	0.1	
2	3	0.1	3	3	0.1		0.3		0.1	4		0.1	1.2	
2	4	0.1	0.3	0.1		0.1			0.1	0.1		0.1		
3	1	0.1							0.1	0.1		0.1	0.1	
3	2	0.1	2.5	3.4			0.1		0.2	0.9		0.3	4.5	
3	4		0.1	0.1						0.1		0.1		
4	1					0.1								
4	2		0.4	0.4	0.1								0.5	
4	3		0.1	0.8						0.1			0.1	
5	1	0.1											0.1	
	Transition Accuracy	45												
	Change Accuracy	59												

Note: 1= Tree, 2= Shrub grass, 3= Bare ground, 4= Urban, 5= Water. Yellow = Pixels where the reference and classified data had not changed and are correct; light green = pixels whose reference and classified data did not change but are incorrect; rose = pixels whose reference data did change but the classified data did not; lavender = pixels that had reference and classified data changed but were incorrect; turquoise = pixels that had reference and classified data changed and are correct; purple = pixels where reference data was unchanged but the classified data changed.

Table 5-20: Summary of the 2000-2005 transition error matrix

		Correct Transition	Error in Transition		Percentage of the sample						
2000	2005		No Change	Change	Correct No Change	Correct Change	Error No Change	Classification Error	False Positive	False Negative	Total
Tree	Tree	66.5	7.2	26.4	6.7		0.7			2.7	10.1
Shrub grass	Shrub grass	44.8	14.6	40.6	6.8		2.2			6.1	15.1
Bare ground	Bare ground	57.2	8.6	34.2	18.6		2.8			11.1	32.5
Urban	Urban	77.6	13.2	9.2	1.7		0.3			0.2	2.2
Tree	Shrub grass	16.6		83.4		0.9		1.5	3.0		5.4
Tree	Bare ground	12.5		87.5		0.1		0.3	0.2		0.6
Tree	Urban							0.3	0.4		0.7
Shrub grass	Tree	23.0		77.0		1.0		0.6	2.6		4.2
Shrub grass	Bare ground	33.6		66.4		4.0		1.7	6.2		11.8
Shrub grass	Urban							0..5	0.4		1.0
Bare ground	Tree	22.7		77.3		0.1		0.1	0.3		0.6
Bare ground	Shrub grass	37.7		62.3		4.5		1.5	6.0		12.0
Bare ground	Urban							0.2	0.2		0.4
Urban	Tree							0.1			0.2
Urban	Shrub grass							0.5	0.9		1.4
Urban	Bare ground							0.2	0.9		1.0
Water	Tree							0.1	0.1		0.2
Total					33.8	10.6	6	7.1	21.2	20.1	99.4

5.7 Improvement of the Estimation

The result of the transition matrices (Tables 5-16 and 5-19) indicated large transition errors especially related to the transition between the shrub grass and the tree categories. Other similar problems were seen in the spatial analysis of the urban category (section 5.4.4) where many of the urban pixels were incorrectly classified. Thus an attempt was made to improve the estimate derived from the analysis.

The improvement of the transition accuracy or the land cover change estimates can be according to the following: (1) identifying false errors such as false positional and the changes that are least likely to occur (van Oort, 2007; Mas, 2005; Woodcock et al., 2001, Congalton and Green, 1999). When such errors are identified, they could then be replaced by their most likely true status. (2) Use available data, that is, confusion and the transition matrices, to develop probabilities which can then be used to make the estimate of land cover (van Oort, 2005; Pontius and Li, 2008). (3) Adjust the misclassification in the confusion matrices by redistributing the errors, as in the so called direct method in Bird et al (2000).

According to the transition error matrices (Tables 5-17 and 5-20) false errors accounted for about 40% of the transition area. In order to deal with this error, three approaches were investigated: one way is to conduct additional field survey focusing on the areas that indicted significant errors or land cover classes that that had large misclassification errors between them. The second is based on earlier analysis of gain (Tables 5-5 and 5-6). One of the outcomes of the gain analysis was the understanding that some changes are due to random chance (Pontius et al., 2004). The application of this concept is subject to further investigation because the gain analysis was based on the whole area of study while the computed false accuracy was based on sampling. In addition to the application of the gain analysis, is the consideration of the reliability of the reference data. Thus if the reference data are 100% accurate then false error can be eliminated by changing the false error to reflect the reference data. These suggestions are subject to future investigation and expansion. A third suggestion is to transfer the concept from the direct method to the transition error matrix, in this case the transition error is redistributed according to their proportion in the reference data (this was briefly considered in the Appendix C). In the subsection below the direct method was applied in order to obtain a better estimation of the categories at each of the time periods.

5.7.1 Result from the Direct Method

The confusion matrix and the transition matrices both express errors, this affects the estimate of the land cover, therefore to remove such effects, the error is redistributed. One such method that redistributes the errors is the direct method (Bird et al. 2000). The method first determines the proportion of each of land cover r_i in a classified class w_j thus, $p(r_i / w_j)$ which can be obtained from Equation 5-4.

$$p(r_i / w_j) = n_{ij} / N_j \qquad \textbf{Equation 5-4}$$

Where n_{ij} is the number of observations in the *i*th land cover class representing ground observations that also occurred in the *j*th land cover (classified) and N_j is the total observations in the *j*th land cover class.

The area estimated (A_i) is given by the sum of the product of the proportion of the land cover and the total number of pixels (T_j) belonging to class j and can be expressed as:

$$A_i = \sum p(r_i / w_j) T_j \qquad \textbf{Equation 5-5}$$

The area of the *i*th class with 95% confidence interval can be expressed as:

$$A_i \pm 1.96(Var(A_i))^{1/2} \qquad \textbf{Equation 5-6}$$

Where

$$\mathrm{Var(Ai)} = \sum (\mathrm{T_j})^2 \,\mathrm{Var(p(r_i} / w_j)) \qquad \textbf{Equation 5-7}$$

and

$$\mathrm{Var(p(r_i} / w_j)) = \mathrm{p(r_i} / w_j))[1 - (\mathrm{p(r_i} / w_j)] / N_j) \qquad \textbf{Equation 5-8}$$

The concept above is limited to the use of confusion matrices and the estimation of the quantities of the land covers at one time in a summary form which limits analysis to obtaining just the differences in the land cover.

From the sum of each land cover (Table 5-2) and their confusion matrices a matrix of proportion was computed (Table 5-21). This provided the proportion of each component of the classified land covers. The area components for each classified class were the product of the area of a spectral class and the proportion of the class along the row, meaning, for example, that the classified area of tree was made up in parts by the proportions along its row. The adjusted area therefore is the sum of that class from the other classes that sum along the row.

Table 5-21: Example of a matrix of proportion for 1986

	Tree	Shrub-Grass	Bare ground	Urban	Water
Area (ha)	**108493**	**172595**	**217807**	**6159**	**190**
Matrix of proportion for area computation					
Tree	**0.7173**	**0.2330**	**0.0412**	**0.0043**	**0.0043**
Shrub-Grass	**0.0800**	**0.5598**	**0.3522**	**0.0073**	**8**
Bare ground	**0.0035**	**0.1818**	**0.8140**	**7**	**0**
Urban		**0.0274**	**0.0411**	**0.9315**	**0**
Water		**0.2500**	**0**	**0**	**0.7500**
Adjusted Area (ha)	**92391**	**161692**	**242810**	**7607**	**744**
Matrix of proportion for variance computation					
	3	**3**	**1**		
	1	**2**	**2**		
		1	**1**		
		4	**5**	**9**	
		0.0234			**0.0234**
CI at 95% (ha)	**4502**	**7303**	**6562**	**1075**	**592**
As % of the adjusted area	**4.9**	**4.5**	**2.7**	**14.1**	**79.5**

The above procedure was used to adjust land cover areas of the three years. The changes between them are outlined in Tables 5-22 and 5-23. The result from the gross change for the two periods 1986 to 2000 and 2000 to 2005 are 2% and 3%. The main objective of this method was to redistribute error, it will require additional procedures to improve its effectiveness.

Table 5-22: Land cover change derived from classification adjusted by the direct method

	1986-2000			CI at 95% (%)	
	No Change	**lost**	**Gain**	**1986**	**2000**
Tree	**88801.70 (17.58)**	**3589.63 (0.71)**		**4.87**	**5.38**
Shrub	**161691.84 (32.00)**		**9237.10 (1.83)**	**4.52**	**4.40**
Bare ground	**237340.22 (46.98)**	**5469.69 (1.08)**		**2.70**	**2.86**
Urban	**7606.69 (1.51)**		**394.83 (0.08)**	**14.14**	**19.84**
Water	**171.69 (0.03)**	**572.61 (0.11)**		**79.53**	**195.83**
Total	**495612.14 (98.1)**	**9631.93 (1.9)**	**9631.93 (1.91)**		

Note:CI = Confidence Interval. Figures in brackets are percentage of the total area

Table 5-23: Land cover change derived from classification adjusted by direct method

	2000 - 20005			CI at 95% (%)	
	No Change(ha)	**Lost(ha)**	**Gain(ha)**	**2000**	**2005**
Tree	**88802 (17.58)**		**4892 (0.97)**	**5.38**	**5.00**
Shrub	**170929 (33.83)**		**10766 (2.13)**	**4.40**	**4.28**
Bare ground	**2204144 (3.63)**	**16926 (3.35)**		**2.86**	**3.28**
Urban	**8002 (1.58)**		**1440 (0.28)**	**19.84**	**19.17**
Water		**172 (0.03)**		**195.83**	
Total	**488146.08 (96.62)**	**17097.99 (3.38)**	**17097.99 (3.38)**		

Note:CI = Confidence Interval. Figures in brackets are percentage of the total area

5.8 Supplementing local land cover analysis with an existing global dataset

In chapter one the issue of lack of land cover data was discussed especially for places such as Nigeria and whether available global data, for example, the NOAA AHVRR NDVI could provide supplementary data at a local level. The data available was the 8 km spatial resolution NDVI obtained from the Data African Dissemination service (USGS, 2004), extracted from the Global Inventory Modelling and Mapping Studies (GIMMS)) and was available from 1982 as a 10 days maximum value NDVI composite.

In order to assess its usefulness for local study the question of the applicability of the NDVI to local study was rephrased to whether the pixels within the study area varied significantly to provide some form of land cover related discrimination. The question was approached from two dimensions, spatially and temporally. The objective of testing whether there was spatial variability in the NDVI pixels was to find out whether on any single date the pixels in the study area differed significantly, since it is the differences that remote sensing methods exploit in their analysis of land cover. Rather than testing the mean of a single date, since the NDVI data follow the same pattern (later shown in Figure 5-20). The test was conducted for all the pixels in the area of study then an analysis of variance was conducted (ANOVA) by approximating the NDVI data to the normal distribution (de Beur and Henebry, 2004). The result indicated no significance difference between the mean of the pixels (Figure 5-18).

The NDVI data set for each were then smoothed to remove the impact of abnormal NDVI values (Figure 5-17) using the Timesat software (Jonsson and Eklundh, 2004) and then, the profiles of five points from the same year were compared in order to visually investigate their differences according to time and regions of the study area (Gamawa-Jakusko plain, Fadama, Potiskum plain, Gudi-Jonga hills and Potiskum town). The profiles indicated that from January to April (Figure 5-18, dekad 1 to 12) and November to December (Figure 5-18, dekad 31 to 36) the profiles were not different. However, slight differences could be seen during the rest of the year (that is the rainy season). The best separation between the five profiles could be seen about the time they attended their peaks (Figure 5-18, dekad 25 and 26, that is, in September). The profile for the pixels in the Gudi-Jonga hills was higher compared to the rest from dekad 12 to 28, that is, the end of April to October. The implication of the analysis was that there was no difference in the NDVI data amongst three of the four regions, thus there was no meaningful separation of land cover at that scale. However some distinction between part of the Guji-Jonga hills could be made with the rest of the study area, not necessarily following the regional boundary (Figure 1-1). Thus the behaviour of such pixels could be monitored over time.

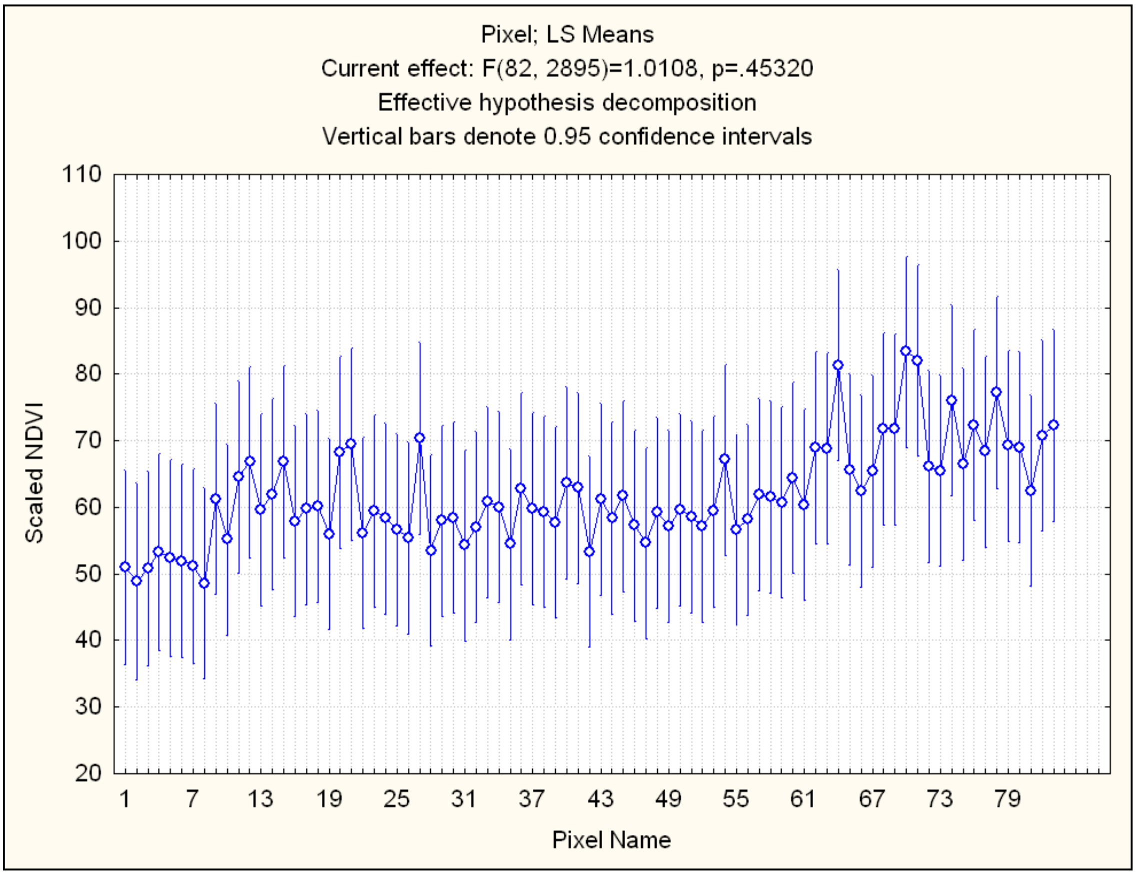


Figure 5-16: Result of test of the means of the 8 km NDVI pixels in the study area (2005)

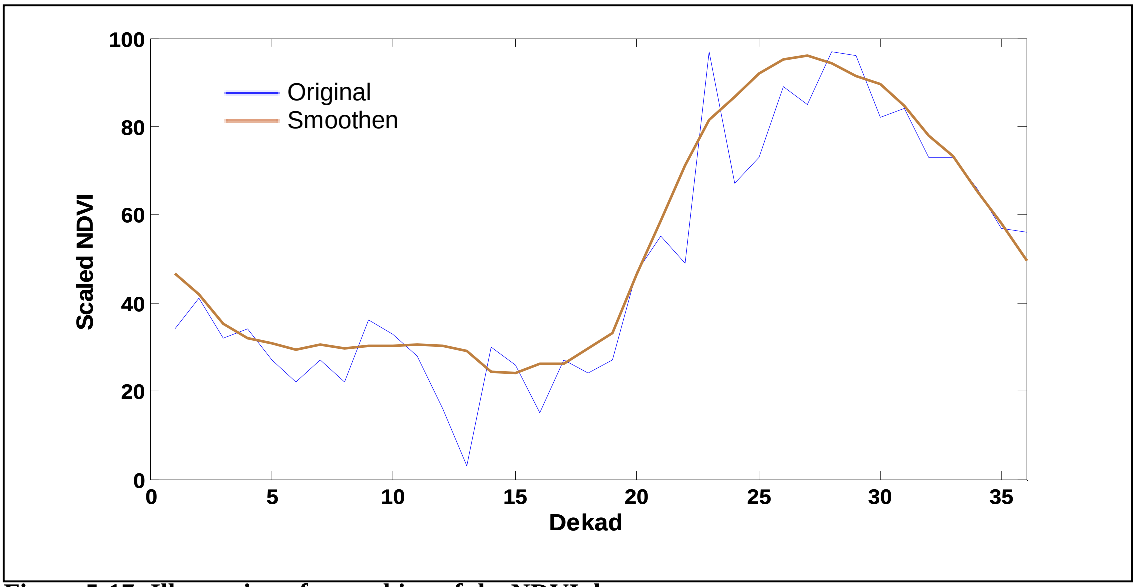


Figure 5-17: Illustration of smoothing of the NDVI data

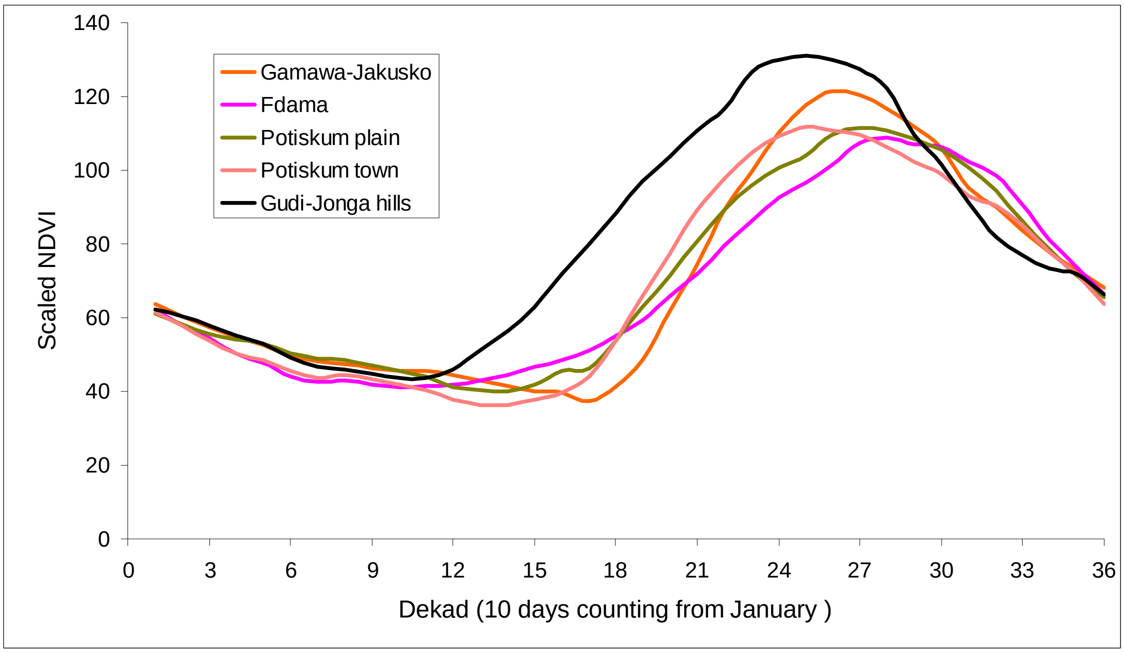


Figure 5-18: Comparison of NDVI profiles in the regions of the study area (2000)

Figures 5-19 and 5-20 compared the profile of pixels at the same location for the three years of the images used in the earlier classifications (chapters 3 and 4) and also compared the acquisition time of the two Landsat images and the NigeriaSat-1 on the profile. The objective of the former was to find out how the values of the same pixel varied in each of the three years and in the latter objective to relate the timing of the image used in the classification and the result of the classification.

The profiles were analysed in line with NDVI profile characteristics: the annual cycle that relates to the season of the study area (Figures 5-18 to 5-20). The profiles were used here as indicators of vegetation vigour, thus 1986 had its vegetation vigour earlier than 2000 and 2005, it also had a higher peak (Figure 5-19) than the others which was not noticed in the southern part (Figure 5-10).

In relation to the time of acquisition of the images, the 1986 image was further from the peak NDVI compared to the 2000 and 2005 images, but the latter lacked the cumulative effect of the 1986 image. The 2000 and 2005 images also came later. The timing and the profile behaved differently in the southern part. There the image timing was at a different time of vegetation vigour. The implication could be important for land cover such as grass that has shorter life considering the climatic condition of the study area. This could probably be the reason for the poor classification of the shrub grass class, meaning that some of the classes observed in the field as grass could actually be senesced grass and thus not living grass if the images had been captured earlier.

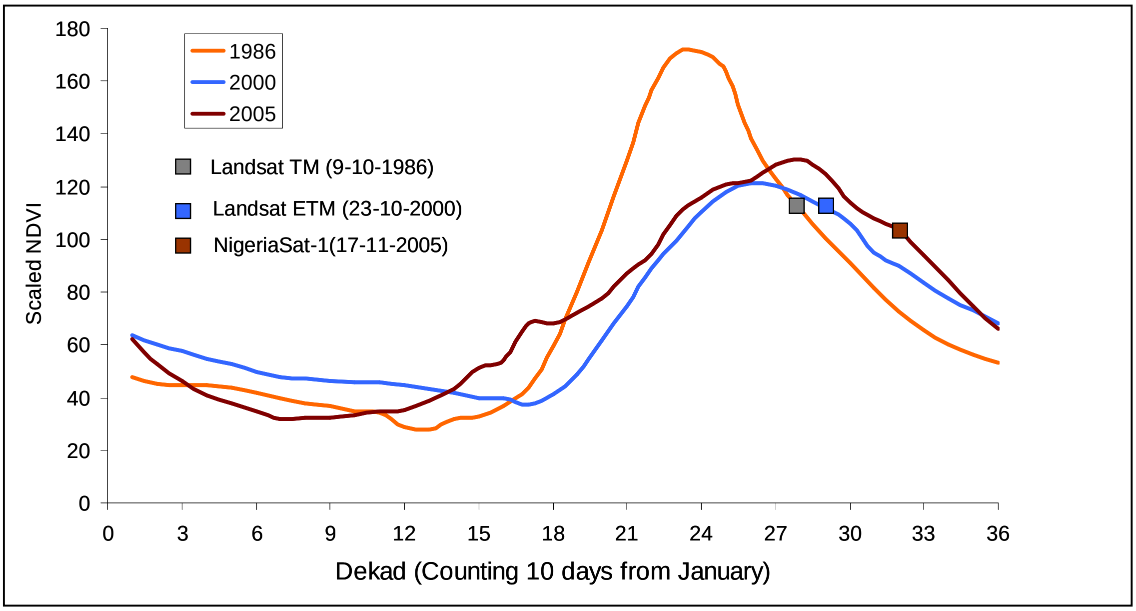


Figure 5-19: Comparison of the 1986, 2000 and 2005 profiles of a pixel in the Gamawa-Jakusko plain and timing of the acquisition the satellites used in the main analysis

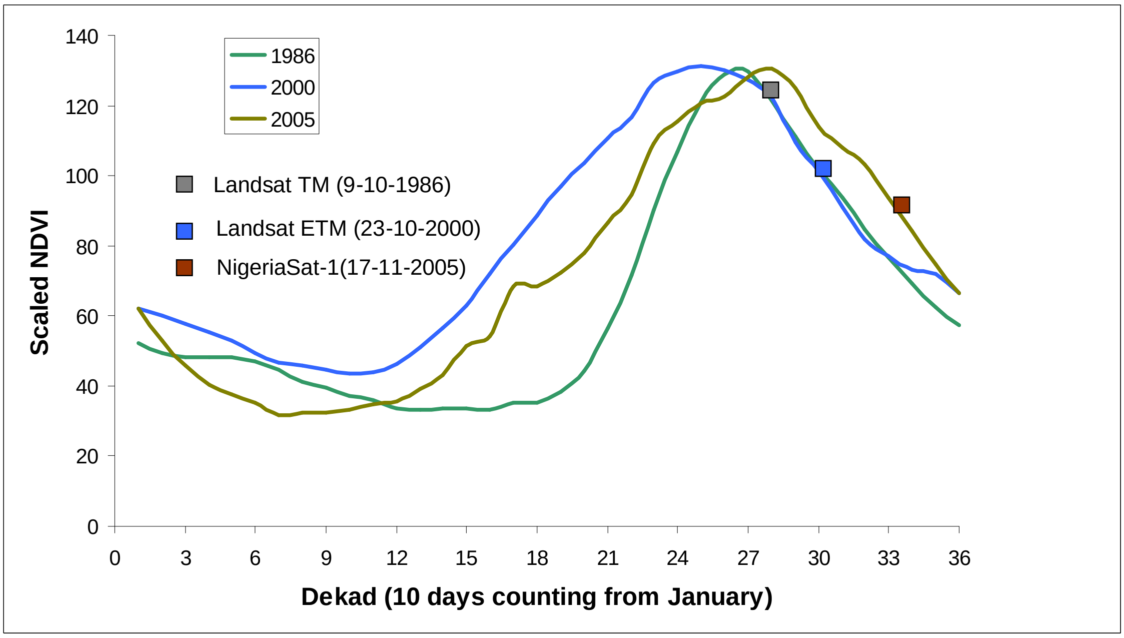


Figure 5-20: Comparison of the 1986, 2000 and 2005 profiles of a pixel in the Gudi-Jonga hills and timing of the acquisition the satellites used in the main analysis

5.9 Summary and conclusions of the analysis of land cover change

From the classification of the NigeriaSat-1 (2005), Landsat ETM+ (2000) and Landsat TM (1986), the area of each of the four land cover categories were deduced and presented first in simple form with their respective net changes, and then in a transition matrix in which the transition between land cover was illustrated.

The transition was analysed in terms loss, gain and persistence, and also in terms as to whether the changes that occurred were random or actual (gain, loss analysis). 61% and 63% of the combined land covers remained unchanged between 1986 and 2000 and 2000 and 2005, respectively. Fourteen percent (half of the computed swap area) of the area of study occupied by shrub grass was lost both in 1986 and 2000, but were gained in the subsequent time by the same amount at another location. A similar large swap was seen in the change of bare ground (11%). Most of the exchanges occurred between shrub grass and bare ground.

The characteristic of change was further analysed graphically and according to the regions of the study area in terms of regional change density for each land cover separately. A major loss of trees was identified between 1986 and 2000 within the Fadama as pockets of concentrated loss, and in the southern part of the study area, that is, the Gudi-Jonga hills where the loss was more general rather than the pocket losses seen in the Fadama. However there were noticeable rises in concentrations of loss in the 2000 to 2005 transition. The selected visual analysis of the shrub grass related to it's loss between 1986 and 2000 in the northern part of the study area and gain by 2005, which spread across the study area.

The gain of bare ground by 2000 was approximately the same location as the loss of shrub grass: Regional change density analysis indicated that intensity of the changes had occurred in the Fadama. The analysis of urban land cover was concentrated around Potiskum which indicated an expansion of the town in the eastern direction.

A transition error matrix was used to analyse the errors associated with the transition. False errors in both classifications was found to be high and associated with the shrub grass and the bare ground. An initial attempt and suggestion was made on how to improve the estimation of the change by using the direct method.

This chapter provided a measurement and characterisation of land cover changes. Thus when the government or the people in the north eastern Nigeria discuss change they have a basis to be specific. It identified the locations of the major changes, the intensities of the changes, the estimate of the changes and the errors and the nature associated with the changes. The changes analysed concurred with the perception by the people in the area that the environment (especially the wilderness) had changed. The changes were perceived to be caused by an increase in population and climatic conditions such as drought. The impact of the change such as low farm yield and conflict on land are felt in all parts of study area especially the Fadama which corresponds to the area with high intensity of change. The change analysis conducted could provide valuable information for planning and controlling unwanted changes and can be directed at specific locations. It also provides an example for combining different approaches for analysing changes.

Chapter 6 Conclusions and Recommendations

One of the aims of this research was to provide a systematic analysis of land cover change in part of north eastern Nigeria. The results obtained defined the state of tree, shrub grass, bare ground and urban in 1986, 2000 and 2005 and further analysis demonstrated how the land cover behaved over the period of the study in spite of the difficulties encountered in the measurement and analysis of land over areas. The systematic analysis involved defining persistence of land cover, loss and gain between dates, the transition of each land cover over the three time periods, analysing the regional impact of the changes, analysing the errors involved with the changes identified and attempting to improve the land cover area estimates.

6.1 Developing a reference dataset

It was decided from the outset that field survey was necessary to connect the remote sensing analysis with the real situation on the ground since there were no current maps or aerial photographs of the area. The reference data provided the training material for digital classification and accuracy assessment. They were developed from a systematic unaligned sampling method in which one kilometre squares were randomly selected within every 10 km grid, amounting to fifty within the study area. All the sample squares were surveyed. The main challenge was in locating the sample squares due to limited access. Another problem was the occasional difficulty in assigning the class to the feature due to the heterogeneous nature of the land cover.

Reference data in the cases of the two Landsat images were developed from image interpretation. This was done in relation to the location of the field sample squares. It was also based on the knowledge drawn from the NigeriaSat-1 classification and the field work, and also personal knowledge. In addition the unsupervised classification and the NDVI data of the respective images were used to aid the interpretation.

It was decided to develop a classification typology that drew mainly from Abdalla (1994), Lawan (1996) and Gregorio and Jansen, 2005. The classification scheme had category and subcategory levels. The former provided the broad land category in the study area which included tree, shrub grass, bare ground and urban, and the latter provided the variations within the broad land cover types and included high tree (mixed), orchard, short tree (mixed), short tree (kwargo, *Bauhinia rufescence*), shrub (mixed), shrub (sabara, *Guiera senegalense*), shrub-grass, grass, bare ground, bare ground clay, bare ground gravel, bare rock, urban. The category provides data suitable for the inventory of the major land covers and habitat, the assessment of degradation of forestry (including wilderness), grazing land, expansion of bare ground (which is directly related to cropland), and the identification and expansion of the urban areas. The data is suitable for development of policy that aims to mitigate environmental problems such as degradation, sustainable utilisation of natural resources, planning, and execution and monitoring of such policy. The subcategory was meant to check whether the variations within the categories could be distinguished through digital classification and where such was possible it would enhance the inventory and possible targeting of particular land cover species. However, the use of the subcategory was limited because of the overall accuracy in the classification.

6.2 The classification

The parallelepiped and the maximum likelihood classifiers were used to undertake classification at several levels, testing to see whether the classifications with 13 classes would produce acceptable results. However, this was not successful because of the high misclassification between the shrub grass and bare ground. It could be concluded from the classification that classification with subclasses of tree, shrub and bare ground would not be likely to produce acceptable overall accuracies from the digital classification.

The difficulty in achieving acceptable overall accuracy in the classification of the 13 classes could be explained by the pre classification analysis which showed few exclusive separations in the line plot, no exclusiveness in the histogram plot and showed multimodality in many of the land cover types. Efforts to subset those land covers exhibiting multimodality did not substantially improve the accuracy, thus indicating the heterogeneous nature of the land covers.

In one of the experiments, the pixels associated with the shrub grass were removed from the confusion matrix and the impact was significant thus indicating a possibility that if shrub grass could be spectrally separated it would be possible to obtain a better accuracy for the classification at that level.

In order to have an acceptable overall accuracy the classes were merged, which then produced an overall accuracy of 62%. The misclassifications relating to the shrub grass was still the problem that hindered obtaining a better result. In an effort to ensure that the error arising from either mixed pixels or semantics from the class descriptors was minimised, an unsupervised method was used that refined the pixels used in the training classifiers. Thus with the efforts taken, the errors reported by the confusion matrix were assumed to be mainly due to spectral inseparability. Thus for the two levels of classifications reported further work could be undertaken, In the first case, the method of classification could be changed to a 'soft' classification, that is, using the fuzzy classification method. By this method the difficulties of assigning pixels into hard classes is reduced. This aspect will also require an understanding of how the results produced will be of benefit to other users, such as planners who will want categorical data on land cover and the changes rather than probabilistic data, rather than the image analyst and the remote sensing community.

The second recommendation is to use images captured at the time when the shrub grass is photosynthetically active. The analysis of the NDVI dataset showed that in some locations the timing of the images corresponded to different points on the phenological cycle. However, all the images used in this study were acquired at the time of decline of vegetation vibrancy.

Similarly the classification of the four land cover classes plus water was undertaken with the Landsat ETM+ (2000) and TM (1986) images, first using wavebands 2, 3 and 4 (the equivalent of the NigeriaSat-1), and then the addition of the combinations of wavebands 5 and 7 (to test the effects of adding middle infrared). These classifications produced overall accuracies of between 67% and 72%. The addition of the two wavebands did not significantly improve the classifications, thus the addition of middle infrared to the NigeriaSat-1 for the classification land cover in the north east during the dry season is not likely to improve the overall accuracy although some visual improvement could be noticed in the classification of the urban land cover.

6.3 Land cover change analysis

Land cover change was analysed in three parts: the first looked at the overall changes between the time periods. The second looked at the changes using the transition matrix and were analysed in terms of terms gain, loss, absolute net change, persistence, swap and also assessed whether the change could have occurred by random. The third procedure analysed each land cover separately in terms of its transition at the three separate dates (from 1986 to 2000 to 2005). It utilised a GIS operation in the analysis to produce a matrix and graphical material for the analysis of the entire pixel set that related to a particular land cover. This thus represents another way of analysing land change in the GIS environment. The third method was also used to compute change with respect to the size of the regions which was called regional change density.

There was a loss of 8,000 ha and 19,000 ha net loss of the tree land cover between 1986 and 2000, and between 2000 and 2005, respectively. This meant an annual net loss of 600 ha and 3800 ha, respectively. The shrub grass experienced a net loss of 34,000 ha between 1986 and 2000, that is, 2500 ha annually, but a net gain of 11,500 ha between 2000 and 2005, that is, 2300 ha annually. The bare ground had a net increase of 29,000 ha and 7, 000 ha, that is, annual rates of 2000 ha and 1400 ha in the first period and second period, respectively. The urban land cover tended to a net increase between 1986 and 2000 and a loss between 2000 and 2005 (this analysis was affected by misclassification of the urban pixel).

According to the second part the analysis, 61.5% (15% (tree), 14% (shrub grass), 32% (bare ground) and 0.5% (Urban)) and 63% (13% (tree), 13% (shrub grass), 36% (bare ground) and 1% (urban)) of the land covers remained unchanged between 1986 and 2000 and 2000 and 2005, respectively. However the swap analysis, that is, the loss of a land cover in the first year of change and its equal gain in the subsequent year and at a different location, of the period between 1986 and 2000 showed that 5%, that is, 24,000 ha were tree lost in 1986 but gained in 2000, similarly 14% or 69,000 ha and are shrub grass and 11% or 55, 000 ha are bare ground lost in 1986 but gained in 2000. The swaps between 2000 and 2005 were 11% (tree), 14% (shrub grass) and 13% (bare ground). The persistence of tree and shrub grass decreased from 1986 - 2000 to 2000 - 2005 but increased for bare ground and urban between the periods; and similarly the swap reduced for the tree and the urban but increased for the shrub and the bare ground.

Furthermore, the gain and loss analyses indicated that when tree gains it replaces shrub grass and urban but not bare ground and when tree is lost it is replaced by shrub grass and urban but not bare ground; when shrub grass gains it replaces bare ground but not tree, it does replace urban between 2000 and 2005 but not between 1986 and 2000; when bare ground gains it does not replace the tree and not the urban between 1986 and 2000 but replaces shrub ground, and when it had losses it was replaced by bare ground and urban; the gain by urban replaces tree only between 1986 and 2000 and replaces both tree and shrub grass between 2000 and 2005 and when it had losses it was replaced by both tree and shrub grass but not bare ground.

The third part analysis was a relative proportion between the transition categories thus the percentage expressed were in relation to the sum of the pixels of the land cover in the three years. Hence 57% of the tree persisted from 1986 to 2005, 16% (1986), 10% (2000) and 5% (2000) was gained and lost, 3% was lost in 1986 but regained in 2005, and 5% was gained by 2005. The shrub grass had different characteristics with low persistence (17%), very high loss (30% by 1986), high recovery (11% lost by 1986 and gained by 2005) and high new growth (19% by 2005). In the case of the bare ground there was high persistence (51%), more gain (29%) from 2000 to 2005 than the loss (9%) from 1986 to 2000. The urban showed a 29% persistence, 28% new growth by 2000 which persisted to 2005 and 26% new growth by 2005.

There was evidence of an increase in pockets of intensive loss of tree between 1986 and 2000 within the Fadama. This kind of loss was less in the southern part of the study area, that is, the Gudi-Jonga hills where the losses seen were more generally spread. However, there were noticeable increases in pockets of concentration of loss in the 2000 to 2005 transition. The same type of analysis of the shrub grass indicated large concentrated losses between 1986 and 2000 in the northern part of the study area. The graphical analysis of the shrub grass showed a general spread covering most parts of the study area except the Gudi-Jonga hills region. The analysis of the bare ground indicated that its gain by 2000 was in approximately the same locations as loss of shrub grass. The analysis of urban land cover was concentrated around Potiskum which indicated an expansion of the town in the eastern direction. The regional change density analysis indicated the Fadama had more changes than any of the other regions.

The results from Abdalla (2004) which assessed changes in land use and cover between 1972 and 1987 could not be compared because of the different location in north eastern Nigeria, the use of a land use based classification system and change analysis methodology. However Braimoh (2006) provided a better analysis of change but at a different location (northern Ghana). The analysis in this work shows a more stable land cover than reported by Braimoh (2006) in which the persistence was 38% unlike the greater than 60% found in this study and the sum of the swap in Braimoh (2006) was 84% while the swap in this study was 60%.

Other studies such as Salami (1999), Mengistu and Salami (2007) and Mertens and Lambin (2004) that would have provided means of comparison were conducted in the rainforest areas though the studies indicated that degradation of forestry, they were however conducted under different climatic condition. Taylor et al (1996) did work to establish the viability of using a remote sensing data in Africa as was well established in Europe at that time, in that wise therefore this work is a further proof of the viability of remote sensing as means of land cover studies. The work of Diouf and Lambin (2001) in the arid region of Senegal indicated decrease in the resilience of vegetation, rain-use efficiency and modification in floristic composition provided an agreement based on similar climatic zone. The work of Alrababah and Alhamad (2006) also in the arid area (but Jordan) showed that Landsat image can be used to provide land cover and land use data for natural resource management. However none among the literature consulted characterised the changes as Braihmoh (2006) or this work.

6.4 Error matrix

The confusion matrices and the transition matrices were the two main tools of analysing error in the work. The confusion matrix was used to judge the classification. Thus when the classification of the 13 classes produced an overall accuracy of less than 60% a better method was sought. The overall accuracy of the four merged classes provided such accuracies. The confusion matrix was also used to compare whether an addition of NDVI or other refinement processes would improve the classification.

Similar to the confusion matrix a transition error matrix was used to analyse the errors associated with the transition. Two summary accuracies were reported: transition (51% and 45%) and change (64% and 59%) accuracy for 1986 to 2000 and 2000 to 2005, respectively. The analysis indicated that most of the error in the transition arose from false errors relating to shrub grass and the bare ground categories, which could be partly corrected.

It is not known how the pixel based error analysis or the sampling size (Binging et al., 1999) has undermined the level of accuracy. Although in some cases a majority filter was applied to the classification, the filter may not produce the real boundary as would have been identified in the field survey, and thus different generalisations were applied to the reference and the classified data.

The main problem in this research was the error associated with the shrub grass. This error could partly be attributed to the timing of the acquisition of the image. The analysis presented here therefore largely represented what happened in the area especially for the other land covers other than the shrub grass.

6.5 The NigeriaSat-1 image

The NigeriaSat-1 image was assessed by its ability to discriminate between land covers and secondly indirectly by the combination of Landsat wavebands that are similar to that of NigeriaSat-1 which could act as a surrogate for the NigeriaSat-1 image. The first assessment indicated that the 13 classes chosen could not be discriminated. Although all the three wavebands of the NigeriaSat-1 image are weak in separating the 13 classes, the infrared provided better separation than the red and the red than the green.

The addition of the two middle infrared wavebands did not significantly improve the overall accuracy of the classification. However visual inspection of the images showed a reduction in the misclassified urban pixels through the addition of the two middle infrared wavebands, thus indicating that the middle infrared could have some usefulness in the classification of urban areas, in addition to its application in moisture and geological related studies.

An effort to obtain a NigeriaSat-1 image for the rainy season period when the vegetation is active was not successful (NASRDA responded that they did not have images during the period because of cloud). This could have provided a means for the discrimination between permanent bare ground and crop land which are all bare ground during the dry season. The crop land could have also provided a means of testing the possibility of crop inventory such as MARS 1 (Taylor et al., 1997). Furthermore, both the crop land and the barren land (unproductive bare ground) could be monitored. The problems observed with especially the shrub grass, could also be reduced with the classification of the image captured during the rainy season.

Thus NASRDA should make an effort to acquire images during the rainy season by taking advantage of the cloud free windows as vital information is lost by the absence of images in this period. The 3-5days temporal resolution and weather forecasting provide such an opportunity. The effort to capture and achieve data for classification and monitoring should include various seasons within a year and year by year. The data captured during the various parts of the year, especially the rainy season would provide an estimation of vegetation, cropland and crop type, changes that occur between seasons and between years. Such data could be useful for managing the impacts of drought and management of natural resources. The effort to collect data all year round will thus increase benefit agricultural and natural resource management in Nigeria and beyond. It also has the potential to fill the gap caused by the failure of the Scan Line Corrector of Landsat-7 ETM+ (Storey et al., 2004).

The operation of the NigeriaSat-1 satellite as part of a constellation that also includes other satellites (Alsat-1, Beijin-1, UK-DMC, Deimo-1 and UK-DMC2) provides the advantage of one day temporal resolution and collection of six scenes in a day, maximising the potential to capture an image over the area of interest. The pricing policing of the imagery was considered appropriate compared to the SPOT image, and although Landsat images are cheaper at the moment their quality is not good due to technical problems with the sensor (Borroffice, 2003; DMC, 2008, pers. comm. Waine, 2008). However, NigeriaSat-1 only has 1 Gb of memory on board, hence only one scene could be acquired in one pass and only 500Mb in 600 seconds can be downloaded as it passes over Nigeria. This limits its operation in frequently acquiring data over Nigeria. A strategy should be developed such that every orbit over Nigeria data is collected by managing the limited window imposed by the memory constraints. The future generation of the NigeriaSat-1 should have enough on board memory to collect data completely along its path over Nigeria every time it passes and have a system of downloading the data immediately (possibly by sending the data to NigComsat-1) after it completion of the path. Presently there is progress towards a NigeriaSat-2 which has a 2.5m panchromatic camera and a 4 band multispectral resolution at both 5m and 32m spatial resolution (Francis, 2007).

6.6 The use of NOAA-AHVRR

Although the 8 km NDVI data set could not be used to provide additional classification data relating to the four classes, it could be used to understand the optimum timing of data acquisition especially with respect to vegetation based land covers. The result of this research could be better by timing for image acquisition at the time when the vegetation is vibrant.

6.7 Dynamics of land cover in north eastern Nigeria

The objectives of this research was successfully pursued and achieved thus providing new understanding of the dynamics of land cover in the north east of Nigeria. It was also able to provide a database for understanding, managing the environmental resources, forestry and problems such as drought, desertification and degradation of natural resources. Land cover studies have limitations as far as the pursuit of a comprehensive understanding of how human use the land and how it changes. While such an endeavour is desirable the main focus of this research was on the land cover change and only limited measurement was undertaken to understand how people perceive environmental changes in the area of study. The changes analysed agreed with the perception of the changes happening in the study area, the changes were perceived to be caused by increases in population and climatic conditions such as drought. The impact of the changes such as low farm yield and hence seasonal migration and conflict over the land were felt in all parts of study area. The various interests in the Fadama (wet and dry season farming, fishing, grazing and the demand for wood from the neighbourhood) corresponded to the computed high intensity of change and thus threatening the survival of the Fadama. The change analysis conducted could prvide valuable information for planning and controlling unwanted changes that can be directed at specific locations. It also provided an example for combining different approaches for analysing changes. Further work would be required to relate specific aspects of the measured changes to people at various locations in the study area.

The land cover change analysis involved the generation of reference data that was used for training the digital classifier and accuracy assessment. The data was setup in two levels addressing broad based data suitable for the purposes of the research mentioned above in this section and for inventory of specific land cover types. This grouping became suitable when the classification of the general and specific land cover types failed to achieve a desirable overall accuracy. Thus by this failure the classification could not provide data on the subcategory but only at the category level. The inability to classify the at the subcategory level with acceptable accuracy means that NigeriaSat-1 imagery is unable to discriminate species of land cover at this location and time, thus some interests of biologists or ecologists may not be met. However, broader interests such as government policy and climate change computation can be informed by the results (e.g. Lambin et al., 2006).

The classification process mainly provided input for the assessment of the land cover changes. It also became the means of testing whether the addition of the middle infrared could be useful in the digital classification of the NigeriaSat-1 image.

The motivation to test the NigeriaSat-1 image was borne out of the potentials of the image especially in Nigeria. Although the test failed to show that the middle infrared would add value to the classification as pursued in this work, that did not diminish its potential, it was rather the experience of obtaining the image that created the impression that the potential of the data was not realised as it was not possible to acquire data at the most crucial time of the year.

Large changes in land cover are occurring in the north eastern Nigeria. There is loss of tree especially in the Fadama and Gudi-Jonga hills with a high intensity of loss in the former. Thus the Fadama is vulnerable and in danger of being lost with high implication for land cover dynamics (Lambin 2006) and the livelihood of people in the neighbourhood of the Fadama, which could cause further migration.

This work analysed changes beyond earlier works by Abdalla (1994) and Lawan (1996) It applied the methods from Pontius et al. (2004) to analyse changes in terms of the transition between years in the two periods, thus providing information on persistence, swapping and whether the changes were random or not. These thus provided an understanding of the changes beyond the net loss or gain as in Abdalla (2004). It also showed that large changes occurred between shrub grass and bare ground. This could be an indication of what will dominate the landscape if there is no intervention including the Fadama. This will make the area vulnerable to desert like conditions, and have an implication on the productivity of the land and hence income of people living in the area, which may in turn lead to conflict and migration.

A further method of analysing land cover using all the classified data at the same time was developed and used generated information on the category of transition with respect to the regions of the study area and the intensity of the changes according to the regions. This further elaborated the changes that had occurred in the area. Large changes in land cover have happened in north eastern Nigeria with impacts on some of the people and the environment leading to the loss of some species of plants and animals, loss of soil fertility, and conflict over resources. The understanding of the changes in the land cover and their implications could help to develop controls such as restriction on tree cutting or mitigation such as tree planting could help reduce the negative impact.

Error of both classification and transition remain an issue in this work, and thus an attempt was made to deal with it. Although this was not successfully achieved this work highlights the need for research in this aspect of land cover change analysis. One way forward would be apply the statistical redistribution errors as in van Oort (2005); van Oort (2007) ;Pontius and Li (2008) and combine it with Binging et al.'s (1999) demand for adequately sampling.

This research is contributing toward a systematic management of the resources. It affirms the perception of the people and government of Nigeria, by quantifying the changes and identifying where changes have occurred. It shows that tree loss occurred in both periods of the study and that the shrub grass changes rapidly which could also by influenced by the time of image acquisition used in the analysis. It also tried to answer questions on land cover change with the limited resources that can be available to any Nigerian research. The change in the shrub grass is directly related to the change in the bare ground. Should the government prioritise the area to manage, the Fadama should get the first priority and followed by the Gudi-Jonga hill area because this is where the tree resources are dwindling. Land cover analysis should go beyond the simple net change or the transition matrix to graphical and spatial analysis of change.

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Appendix A: Metadata of NigeriaSat-1 Image used in this Research

Source
    Imaging Date2005-11-17
    Imaging Time09:13:18
    MissionNIGERIASAT
    Viewing Angle0.0 (DEG)
    Sun Azimuth141.06993049093015 (DEG)
    Sun Elevation51.09397048388079 (DEG)
Raster Dimensions
    Columns18595
    Rows 7711
    Bands 3
Raster Encoding
    Data TypeBYTE
    Number of Bits8
    ByteorderI
Data Access
    FormatGEOTIFF
    Data fileDN0002eeT_L1R.tif
Dataset ID
    Copyright DMC International Imaging Ltd.
Production
    Producer DMC International Imaging Ltd.
    Url:http://www.dmcii.com
    Production Date2006-01-16
    Type
    Job ID
Data Processing
    Geometric1R
    Radiometric Cubic convolution
Coordinate Reference System
    EPSG
        TypeGEOGRAPHIC
        NameWGS 84
        CodeEPSG:4326
        Geographic Coordinate SystemNameWGS 84
            CodeEPSG:4326
            Prime Meridian
            Horizontal DatumNameWorld Geodetic System 1984
                CodeEPSG:6326
                EllipsoidNameWGS 84
                    CodeEPSG:7030
                    ParametersMajor Axis6378137.0 (M)
                      Minor Axis6356752.31424518 (M)

Projection Coordinate Transformation Method Projection Parameters Name Code Value

Raster Coordinate System

Type POINT

Image Display

Red	1
Green	2
Blue	3

	Mean	Stdv
1	50.4076298689565	10.524833663402315
2	39.30018513429468	11.44795538709406
3	49.79206143557154	10.765616689239966

	Min	Max
1	10.0	85.0
2	13.0	80.0
3	24.0	92.0

	Lin Min	Lin Max
1	24.095545710450708	76.71971402746229
2	10.680296666559528	67.92007360202983
3	22.878019712471627	76.70610315867145

Image Interpretation

	Description
1	NIR
2	RED
3	GREEN

	Gain	Bias	Unit
1	0.7163860552402246	0.004207856100751372	W/m2/sr/m-6
2	0.6765611679376768	0.0021975098196290927	W/m2/sr/m-6
3	0.8739763182397806	0.0018370357608093748	W/m2/sr/m-6

Dataset Frame

X	Y
10.150595751349705(DEG)	12.029186931926935(DEG)
10.65821712937201(DEG)	9.788106215763754(DEG)
16.310686065377702(DEG)	10.559890375377655(DEG)
15.848675193172015(DEG)	12.807571496585807(DEG)

Appendix B: Data description of Orthorectified Landsat Enhanced Thematic Mapper Plus Imagery and Landsat Thematic Mapper Imagery

Part One: Orthorectified Landsat ETM+plus
Output Product Specifications:

- • Spectral Bands: All nine Landsat ETM++ bands - 3 visible, 1 NIR, 2 SWIR, 1 Panchromatic, and 2 thermal IR,
- • Coverage: Single Landsat WRS Path/Row,
- • Projection/Datum: UTM / WGS84,
- • Pixel size: 14.25, 28.5, and 57 meters,
- • Interpolation Method: Nearest Neighbor,
- • Absolute Positional Accuracy: 50 meters RMS.

-
Source (Input) Data:

***Imagery*:**

- • Spectral Bands: All nine Landsat TM bands,
- • Coverage: Single Landsat WRS Path/Row,
- • Projection/Datum: SOM / WGS84,
- • Pixel Size: Mixture of 28.5 and 30 meters,
- • Interpolation Method: Cubic Convolution,
- • Orientation: Path oriented,
- • Coverage Date: Scene dependent (nominally 2000 +/- 1 years).

***Control*:**

- • Horizontal: Controlled scenes contained 6 to 12 photo-identifiable points with absolute positional accuracy not greater then 15.0 meters RMS.
- • Vertical: DTM with 3-arc second postings, where available. Where 3-arc second data not available, GTOPO30 (30-arc second) digital elevation models are used.

-

Digital Image Processing:

- • Photogrammetric Block Adjustment:
  Performed using Earth Satellite Corporation's proprietary photogrammetric software.
- • Orthorectification:
  Resampled to a UTM/WGS84 projection using nearest neighbor (i.e. no interpolation).
- • Image Enhancements:
  The data are spatially and spectrally unenhanced.

Part Two: Orthorectified Landsat TM

Output Product Specifications:

- • Spectral Bands: All seven Landsat TM bands - 3 visible, 1 NIR, 2 SWIR, and 1 thermal IR,
- • Coverage: Single Landsat WRS Path/Row,
- • Projection/Datum: UTM / WGS84,
- • Pixel size: 28.5 meters,
- • Interpolation Method: Nearest Neighbor,
- • Absolute Positional Accuracy: 50 meters RMS.

-

Source (Input) Data:

***Imagery*:**

- • Spectral Bands: All seven Landsat TM bands,
- • Coverage: Single Landsat WRS Path/Row,
- • Projection/Datum: SOM / WGS84,
- • Pixel Size: Mixture of 28.5 and 30 meters,
- • Interpolation Method: Cubic Convolution,
- • Orientation: Path oriented,
- • Coverage Date: Scene dependent (nominally 1990 +/- 3 years).

***Control*:**

- • Horizontal: Controlled scenes contained 6 to 12 photo-identifiable points with absolute positional accuracy not greater then 15.0 meters RMS.
- • Vertical: DTM with 3-arc second postings, where available. Where 3-arc second data not available, GTOPO30 (30-arc second) digital elevation models are used.

-

-

Digital Image Processing:

- • Photogrammetric Block Adjustment: Performed using Earth Satellite Corporation's proprietary photogrammetric software.
- • Orthorectification: Resampled to a UTM/WGS84 projection using nearest neighbor (i.e. no interpolation).
- • Image Enhancements: The data are spatially and spectrally unenhanced.

-

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Earth Satellite Corporation

Appendix C: Direct method Applied to the Transition Matrix

In a similar way the direct method (Birds, 2000) used the confusion matrix and the estimate from the classified image in order to redistribute the errors and thus produce new estimates, the same direct method principles was used to re-estimate the transition using the transition error matrix and the transition matrix. The adjustment first assumes the errors in the transition are not from the reference maps; therefore the error arises from the transition of the classified which are distributed in order of the proportion of the reference and in similar ways to the procedure of the direct method. Thus the equivalent of $p(r_i / w_j)$ in Equation 5-5 was obtained for the transition from tables 5-16 to 5-20, i.e. the columns, with the elements of the transition error matrix substituting for N_j in Equation 5-4. A matrix of proportion is illustrated in Table C-1 for 1986-2000. The adjusted estimates for 1986 to 2000, net changes and their standard deviation at 95% confidence interval are in Tables C-2 to 7.

The main drawback of the method at this stage is that after the adjustment the year in the middle i.e. 2000 has two estimations are very different Table.

Table C-1: Matrix of Proportion for the Adjustment of the Transition Matrix 1986 to 2000

Reference:1986		1	2	3	4	1	1	2	2	2	3	3	3	3	4	4	5	5	5	5
Reference:2000		1	2	3	4	2	3	1	3	4	1	2	4	5	1	3	1	2	3	4
Classified:1986	Classified:2000																			
1	1	0.787	0.04	0.001			0.259	0.145			0.367	0.004			0.159	0.006				
2	2	0.034	0.375	0.071			0.152	0.203			0.273	0.161	0.5		0.159	0.163			1	
3	3		0.125	0.653			0.006	0.014				0.217			0.045	0.304	0.5			
4	4			0.001	0.919											0.002				
5	5																			
1	2																			
1	3	0.121	0.042	0.001	0.016		0.392	0.246			0.172	0.017			0.045	0.016				
1	4	0.016	0.011				0.044	0.101				0.019				0.006				
1	5	0.008	0.011	0.004	0.032		0.019	0.072				0.019			0.023	0.002				
2	1	0.005													0.023					
2	3	0.026	0.060	0.007			0.063	0.043			0.125	0.01			0.295	0.044				
2	4		0.175	0.135			0.051	0.145			0.008	0.487	0.25			0.056	0.25			
2	5		0.007	0.031	0.016		0.006	0.014			0.016	0.021	0.25			0.002				
3	1						0.006									0.002				
3	2		0.018	0.002							0.016	0.002			0.068	0.014		1		
3	4	0.003	0.131	0.082				0.014			0.016	0.037			0.182	0.376	0.25			

Table C-1 Continue

	Reference:1986	1	2	3	4	1	1	2	2	2	3	3	3	3	4	4	5	5	5	5
	Reference:2000	1	2	3	4	2	3	1	3	4	1	2	4	5	1	3	1	2	3	4
Classified:1986	Classified:2000																			
3	5		0.005	0.012								0.002				0.008				
4	1																			
4	2				0.016															
4	3											0.004								
4	5			0.001																
5	1																			
5	2										0.008									
5	3																			
5	4																			

Table C-2: Adjusted Land Cover Transition Matrix 1986 to 2000

	1986				
	Tree	Shrub grass	Bare ground	Urban	Water
2000					
Tree	78512	1099	449	9	9
Shrub grass	561	80327	4999	38	481
Bare ground	26773	18499	152198	212	14
Urban	4609	64290	54874	2635	9
Water	3936	7579	2978	158	0
Total (1986)	114391	171794	215497	3051	513

Table C-3: Net Change 1986 to 2000 with Adjusted Estimate

	At 2000	
Total	Net Loss	Net Gain
Tree	34313.96	
Shrub grass	85388.38	
Bare ground	17800.82	
Urban		123365
Water		14138

Table C-4: Standard Deviation (+/-) in Percentage of each Transition Element 1986 to 2000 of Adjusted Estimate

	1986				
	Tree	Shrub grass	Bare ground	Urban	Water
2000					
Tree	2.7	123.0	44.3	0.0	0.0
Shrub grass	0.0	3.4	14.1	99.2	274.4
Bare ground	6.8	8.2	2.1	67.7	0.0
Urban	16.9	3.9	4.5	8.8	0.0
Water	18.2	13.9	22.3	100.0	0.0

Table C-5: Adjusted Land Cover Transition Matrix 2000 to 2005

	2000				
	Tree	Shrub grass	Bare ground	Urban	Water
2005					
Tree	55145	19160	2822	1094	997
Shrub grass	29268	74494	61512	6894	0
Bare ground	4267	44645	178793	6802	630
Urban	4469	4568	2018	7664	0
Water	0	0	0	0	0
Total (1986)	114391	171794	215497	3051	513

Table C-6: Net Change with Land Cover Transition Matrix 2000 to 2005

	At 2000	
Total	Net Loss	Net Gain
Tree	13929	
Shrub grass		29300
Bare ground	10009	
Urban		123365
Water	1627.1	

Table C-7: Standard Deviation (+/-) in Percentage of each Transition Element 1986 to 2000 of Adjusted Estimate

	2000				
	Tree	Shrub grass	Bare ground	Urban	Water
2005					
Tree	**3.9**	**7.9**	**21.5**	**41.0**	**39.4**
Shrub grass	**6.8**	**3.7**	**4.6**	**14.9**	
Bare ground	**19.0**	**4.6**	**1.8**	**16.9**	**51.5**
Urban	**19.9**	**18.4**	**29.4**	**9.6**	
Water					